Evaluating the Operational Impact and Operator User-Experience Mechanisms of a Real-Time, Rule-Based Boarding Route Management System (rtBRMS) in International Airport Gate Operations

Luca Moheb

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University of Worcester

DECLARATION

I, Luca Moheb declare that the work in this thesis was carried out in accordance with the regulations of the University of Worcester and is original except where indicated by specific reference in the text. No part of the thesis has been submitted as part of any other academic award. The thesis has not been presented to any other education institution in the United Kingdom or overseas. Any views expressed in the thesis are those of the author and in no way represent those of the university.

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ABSTRACT

Passenger-flow variability during boarding and deboarding remains a persistent source of turnaround instability at capacity-constrained airports, despite advances in Airport Collaborative Decision-Making (A-CDM) and predictive analytics. Existing research relies predominantly on simulations and controlled experiments, leaving a gap in field-validated evidence on whether real-time automated systems that actively regulate passenger movement can reduce turnaround variability under authentic conditions. Equally, little is known about how frontline staff experience and respond to such systems in their daily work.

This thesis evaluates the operational impact and human-factor consequences of deploying a real-time, rule-based Boarding Route Management System (rtBRMS) in live airport gate operations. The investigation adopts a multi-method quantitative research design consisting of two complementary, integrated empirical investigations. Study 1 establishes what the system does to objective turnaround performance through a 48-stratum quasi-experimental field experiment across 171 short-haul flights at Mashhad International Airport (MHD), with continuous outcomes analysed via Welch t-tests and Type-III General Linear Models, and binary fast-process thresholds analysed via Firth-penalised logistic regression. Study 2 examines how frontline operators, who actively utilise rtBRMS in their daily gate work, experience those changes and how that user-experience shapes their engagement, performance, and satisfaction, through a cross-sectional survey of 224 operators (gate agents, ramp coordinators, supervisors, security personnel, and ground-handling staff) analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with 5,000 bootstrap resamples. Together, Study 1 and Study 2 form a single socio-technical evidence arc from technological intervention to human-factor outcomes, integrated in the discussion chapter.

The operational findings (Study 1) show that rtBRMS reduces Gate Occupation Time by approximately 12 to 13 minutes (Cohen's $d = 4.37$; partial $\eta^2 = .87$), compresses boarding windows by 15.8% and deboarding windows by 8.2%, and increases passenger throughput by approximately 1.6 to 1.7 passengers per minute. Effects are larger at more complex gate configurations and remain consistent across all passenger load levels. The user-experience findings (Study 2) show that perceived flow stability strongly predicts

perceived system predictability (β = 0.584), which drives work engagement, individual performance (R^2 = .573), productivity (R^2 = .662), and system satisfaction (R^2 = .486), with the mechanism stable across roles and experience levels.

The thesis contributes novel field-based evidence that real-time passenger-flow automation can measurably improve turnaround performance under authentic conditions, and provides an integrated explanation of how frontline staff convert stabilised flow into engagement and performance. The findings identify shared-access gates under high passenger loads as the highest-priority deployment contexts, and demonstrate that making system behaviour visible and predictable to operators is as important as the technical performance of the system itself, with direct implications for interface design, staff training, and change management in airports deploying digital operational technologies..

PUBLICATIONS/DISSEMINATIONS ARISING FROM THIS THESIS

The following publications and scholarly outputs have been produced during the course of this doctoral research. Materials, concepts, empirical findings, and analytical frameworks developed in these works have been incorporated into the present thesis where appropriate.

Submitted / Under Review

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CONFERENCE PARTICIPATION AND ACADEMIC ENGAGEMENT

The doctoral research was informed and contextualised through participation in major academic and industry conferences focusing on aviation operations, digitalisation, artificial intelligence, and organisational systems.

World Data Symposium (WDS), International Air Transport Association (IATA),

8-9 April 2026, Singapore.

Scholarly participation in sessions addressing artificial intelligence, data governance, automation, and advanced analytics in air transport operations. The symposium explicitly focused on emerging technologies, including AI and machine learning, relevant to real-time operational decision-support systems examined in this thesis.

15th SESAR Innovation Days (SIDs), SESAR Joint Undertaking,

1-4 December 2025, Lake Bled, Slovenia (hosted by Pipistrel and the University of Ljubljana).

Scholarly engagement with the SESAR research community on air traffic management transformation, turnaround predictability, A-CDM evolution, and execution-layer automation.

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ABBREVIATIONS

A-CDM	Airport Collaborative Decision Making
AI	Artificial intelligence
ANN	Artificial neural network
AOBT	Actual Off-Block Time
APOC	Airport Operations Centre
ATC	Air Traffic Control
ATFCM	Air Traffic Flow and Capacity Management
AUT	Perceived Autonomy
AVE	Average Variance Extracted
CB-SEM	Covariance-Based Structural Equation Modelling
CI	Confidence interval
CR	Composite reliability
CSR	Comparative Superiority of rtBRMS
df	Degrees of freedom
DOA	Degree of automation
EMP	Employee Productivity
ENG	Work Engagement
ETL	Extract–Transform–Load
f^2	Cohen's effect size (PLS structural model)
FSP	Flow-Stability Perception
G/G/1	General inter-arrival/General service, single server
GI/G/m	General independent inter-arrival/General service, m servers
GLM	General Linear Model
GOT	Gate Occupation Time

HAI	Human–Automation Interaction
HMI	Human–Machine Interface
HTMT	Heterotrait–Monotrait ratio
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IGOM	IATA Ground Operations Manual
IS	Information systems
IWP	Individual Work Performance
JD-R	Job Demands–Resources
JSR	Job Stress Reduction
KPI	Key Performance Indicator
MHD	Mashhad International Airport
ML	Machine learning
MLE	Maximum likelihood estimation
NM	Network Manager (EUROCONTROL)
OR	Odds ratio
OTP	On-time performance
PLS-SEM	Partial Least Squares Structural Equation Modelling
PLSpredict	PLS-SEM predictive assessment procedure
PPC	Perceived Performance Contribution
PSP	Perceived System Predictability
Q^2	Cross-validated redundancy (PLS prediction metric)
R^2	Coefficient of determination
RCPSP	Resource-Constrained Project Scheduling Problem
rtBRMS	Real-time Boarding Route Management System

SA	Situation awareness
SD	Standard deviation
SE	Standard error
SOP	Standard operating procedure
SS	System Satisfaction
TAM	Technology Acceptance Model
TAT	Turnaround time
TOBT	Target Off-Block Time
TSAT	Target Start-Up Approval Time
VIF	Variance Inflation Factor
VRPTW	Vehicle Routing Problem with Time Windows
WIP	Work-in-process
η^2p	Partial eta squared

1. INTRODUCTION

1.1 OVERVIEW OF THE CHAPTER

This chapter establishes the foundation for the thesis by setting out the rationale, research gap, and conceptual architecture for investigating real-time, rule-based passenger-flow control in airport boarding operations. Section 1.2 articulates the operational and economic imperatives motivating the study; Section 1.3 identifies the research gap and formulates the problem statement; Section 1.4 presents the research aim and objectives with a traceability matrix linking each hypothesis to its corresponding research objective; Section 1.5 sets out the anticipated theoretical and practical contributions of the thesis; Section 1.6 outlines the thesis structure; Section 1.7 closes the chapter.

1.2 RATIONALE FOR THE STUDY: GROWTH IN AIR TRAVEL AND OPERATIONAL CHALLENGES

Contemporary airport operations face a convergence of accelerating passenger volumes, infrastructure capacity constraints, and intensifying network punctuality requirements that elevate gate-level process stability from an operational concern to a strategic imperative (Eurocontrol, 2019; IATA, 2023). Within this constrained environment, aircraft turnaround operations, particularly boarding and deboarding phases, have emerged as critical bottlenecks that disproportionately influence cycle-time predictability, stand utilisation efficiency, and downstream network stability (Schultz, 2018; Wu and Caves, 2000). This chapter frames the research problem, identifies the gaps in existing knowledge, and presents the aim, and objectives that guide the empirical investigation.

Global air traffic continues to grow at a pace that outstrips infrastructure expansion. IATA's full-year 2025 data show passenger demand up 5.3% year-on-year and a record load factor of 83.6%, with capacity expansion lagging behind demand at capacity-constrained airports worldwide (IATA, 2026). Eurocontrol's 2025 summer review confirms that approximately one in four flights still experienced ATFM delays of 3 to 5 minutes, with capacity shortfalls and weather as the dominant constraints (Eurocontrol, 2025). Long-range forecasts indicate a doubling of passenger movements by 2037,

amplifying the operational consequences of even minor process deviations (ICAO, 2018; Airports Council International, 2020).

The operational significance of gate-level passenger-flow variability extends beyond local delays to systemic network effects. Boarding-phase delays exceeding 10 minutes occur in 15 to 25% of short-haul operations at major European hubs, generating cascade effects across tightly coupled schedules (Eurocontrol Performance Review Unit, 2022; Fricke and Schultz, 2009) and imposing annual delay costs exceeding €5 billion in Europe alone (Cook et al., 2021). Process-mining of turnaround event logs confirms that milestone predictability depends on the stability of upstream flow processes, with persistent boarding-phase variability undermining mature A-CDM regimes (Rott, Schultz and Fricke, 2023). Machine-learning prediction models forecast turnaround milestones with growing accuracy, but they monitor and predict rather than actively regulate the passenger movement that generates variability at source (Okwir, Amouzgar and Ng, 2025; Tang et al., 2025). The stochastic nature of passenger behaviour, namely heterogeneous arrival patterns, variable walking speeds, unpredictable baggage handling, and spatial interference at chokepoints, propagates variance through serial dependencies that conventional prediction systems cannot eliminate (Steffen and Hotchkiss, 2012; Schultz and Fricke, 2011).

Concurrently, digital transformation has shifted aviation operations from manual coordination to human-automation collaboration (Endsley, 2017; Parasuraman and Manzey, 2010). The same shift is observable across other safety-sensitive operational domains: in access control, for example, the integration of artificial intelligence into physical security systems has moved organisations from rule-coded mechanical actuation toward AI-mediated authorisation that combines real-time risk inference with human supervisory control, illustrating how execution-layer automation in operational settings depends on the joint optimisation of technical capability and human acceptance (Moheb et al., 2026).

Frontline staff perceptions of automated systems, particularly predictability, autonomy, and usefulness, shape engagement, performance, and satisfaction, with effects pronounced in time-critical, safety-sensitive environments (Bakker and Demerouti, 2007; Venkatesh et al., 2003; DeLone and McLean, 2003). This convergence of operational and human-factor imperatives establishes the basis for evaluating real-time, rule-based flow-control technologies through human–automation interaction frameworks that account for both system-level performance and operator-level outcomes.

1.3 RESEARCH GAP AND PROBLEM STATEMENT

1.3.1 The Turnaround Process and the Limits of Current Digital Approaches

Airport operations are tightly coupled socio-technical systems characterised by high interdependence, temporal constraints, and limited buffers, where predictable passenger movement is a prerequisite for on-time performance, stand utilisation, and network stability (Perrow, 1984; Fodness and Murray, 2007; Evler et al., 2022). Within the turnaround sequence (deboarding, cabin cleaning, catering, fuelling, boarding, pushback), boarding and deboarding dominate cycle-time variability in short-haul operations: passenger-flow irregularities, heterogeneous behaviour, and spatial constraints at shared-access chokepoints induce congestion that propagates along the critical path (Steffen and Hotchkiss, 2012; Schultz and Fricke, 2011; Wu and Caves, 2000). Time-motion studies and discrete-event simulations consistently identify boarding as the longest and most variable subprocess, with durations of 10 to 35 minutes for narrow-body aircraft (Nyquist and McFadden, 2008; Schultz, 2018; Ferrari and Nagel, 2005).

Queueing theory explains how this variability inflates cycle time. Little's Law relates cycle time, work-in-process, and throughput (Little, 1961); Kingman's formula shows that as utilisation approaches capacity, even modest variance in interarrival or service times drives non-linear growth in waiting (Kingman, 1961; Whitt, 1993). In serial systems such as door-tunnel-aisle flows, upstream variance compounds downstream through the variability propagation law (Hopp and Spearman, 2011). Empirical work confirms these predictions: boarding-time variance grows super-linearly with load, and

aisle interference inflates mean boarding duration by 30 to 50% relative to unimpeded flow (Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015).

A-CDM frameworks, integrated dashboards, and ML-driven prediction models have substantially improved milestone visibility at major hubs, with reported 15 to 30% reductions in taxi-out delays and 5 to 10% gains in on-time performance (Eurocontrol, 2017; SESAR Joint Undertaking, 2016; Guo et al., 2020; Kuster and Jannach, 2006). These technologies, however, do not address the root cause of variability: uncontrolled passenger flow at gate-area chokepoints, where stochastic arrivals create transient congestion that cascades into delay (Schultz and Fricke, 2011; Moreira et al., 2023; Tang et al., 2025).

Why these advances have not resolved gate-level variability becomes clear when three levels of digital intervention are distinguished. Digitisation converts records into digital form. Digitalisation deploys real-time information systems and predictive analytics that forecast turnarounds and recommend reallocations (Lee and Yu, 2018; Guo et al., 2020; Evler et al., 2022); these systems remain fundamentally observational, telling controllers a delay is likely without preventing the flow irregularities that cause it. Execution control is qualitatively different: it acts on flow states in real time, pacing release through door actuation, coordinating routing across shared-access corridors, and enforcing congestion-avoidance rules that align inflow with downstream aisle capacity (Gehlen and Ronzani, 2025; Rott, Schultz and Fricke, 2023; Okwir, Amouzgar and Ng, 2025; Tang et al., 2025). Only execution-layer automation can suppress variance at its source. This thesis evaluates a real-time, rule-based Boarding Route Management System (rtBRMS), defined here as an event-driven controller that operates at the execution-control level by (i) actuating door states in response to live tunnel and aisle congestion signals, (ii) coordinating topology-aware routing across more than 60 access nodes to prevent cross-stream interference, and (iii) enforcing pre-validated congestion-avoidance rules (occupancy, service-rate, and clearance thresholds) that hold work-in-process within control limits. The mechanism is developed fully in Chapter 2.

1.3.2 Problem Statement

The core difficulty addressed by this thesis can be stated in a single sentence: the variance that drives short-haul turnaround instability is generated locally at the gate by stochastic passenger behaviour, propagates non-linearly through a tightly-coupled serial process, and cannot be neutralised by any of the digital interventions currently available to the industry, because none of those interventions act on the physical flow that produces it. Boarding and deboarding alone account for 60 to 70 percent of turnaround-time variance in short-haul operations (Rott, Schultz and Fricke, 2023; Schultz, 2018), and Section 1.3.1 has shown that this variance is a property of the gate environment itself: heterogeneous walking speeds, unpredictable carry-on stowage, shared-access tunnels, and peak-load surges produce burst arrivals that exceed aisle service capacity and inflate cycle time non-linearly through the queueing dynamics formalised by Kingman (1961) and Little (1961). Variance, in this regime, is not a residual problem that can be cleaned up after the fact; it is the dominant feature of the operating environment, and it regenerates continuously as long as nothing acts on the flow that produces it.

This makes the difficulty structural rather than incidental. Airport Collaborative Decision-Making (A-CDM), milestone-driven coordination, and machine-learning prediction of turnaround durations have all been deployed against this variance over the past two decades, and they have collectively improved milestone visibility, partner coordination, and forecast accuracy (Eurocontrol, 2017; Okwir, Amouzgar and Ng, 2025; Tang et al., 2025). What they share, however, is that they are observational. They make variance visible and forecastable; they do not intervene in the upstream physical process that generates it. Process-mining analyses of mature A-CDM deployments confirm the consequence: even under disciplined milestone exchange, turnarounds continue to follow dozens of distinct process variants and miss Target Off-Block Time targets in 35 to 45 percent of cases (Rott, Schultz and Fricke, 2023; De Falco et al., 2023). Prediction has improved; realisation has not. The industry knows when variance will occur but possesses no validated means of preventing it at source. This is the prediction-execution gap, and it is a structural property of the existing intervention portfolio rather than a deficiency of effort.

The core difficulty therefore narrows to a single proposition: only an intervention that acts on the flow itself, in real time, at the door-tunnel-aisle interface where variance is born, can break the regenerative cycle. Execution-layer automation, namely a real-time controller that paces door release, routes shared-access streams, and enforces congestion-avoidance rules in response to live occupancy signals, is the only intervention class that satisfies this criterion. Yet execution-layer automation is also the most demanding form of digital intervention to deploy successfully in a live gate environment, because it changes the rhythm of frontline work, alters the locus of micro-decision authority, and depends entirely on the operators who must enact it daily to recognise its actions as predictable, accept its outputs as useful, and convert its stabilised flow into engaged and productive behaviour. The capability that addresses the core difficulty therefore cannot be deployed in isolation from the people who run it.

The problem this thesis addresses follows directly from this coupling. A system that suppresses variance at the door but is experienced by operators as opaque, autonomy-threatening, or unreliable will fail to achieve sustained adoption and may even degrade performance through workarounds, disengagement, or reversion to manual procedures (Bainbridge, 1983; Parasuraman and Riley, 1997). A system that operators perceive as predictable, supportive, and performance-enhancing will generate the engagement and behavioural integration necessary for sustained operational effectiveness (Bakker and Demerouti, 2007; Lee and See, 2004). The operational mechanism and the operator user-experience mechanism are therefore not parallel research interests but two sides of a single coupled problem: the operational gain at the gate is realised only through the cognitive and motivational responses of the people who run it, and the operator user-experience response is meaningful only if the system has actually changed operational conditions. Evidence on either dimension alone is insufficient. Evidence on the technical side without operator user-experience evidence cannot establish whether the gain is sustainable in practice; evidence on the operator user-experience side without technical evidence cannot establish whether operators are responding to a real change or to expectation alone (Halpern and Mwesiumo, 2021; Venkatesh, Brown and Bala, 2013).

The research problem this thesis addresses is therefore dual by necessity rather than by design. Airports require, simultaneously, field-validated proof that real-time, rule-based passenger-flow automation measurably improves queue-sensitive turnaround performance under authentic operational heterogeneity, and a mechanistic explanation of how frontline operators perceive, internalise, and respond to stabilised flow through pathways that drive engagement, individual work performance, productivity, and system satisfaction. Neither half of this requirement is optional, and neither can substitute for the other; the dual-evidence architecture of this thesis is the form the answer must take when the core difficulty is properly stated. The term operator user-experience dimension, used throughout this thesis, refers to these cognitive and motivational responses of frontline staff to automated systems: how they perceive system predictability, experience changes in autonomy and workload, and translate those perceptions into engagement, performance, and satisfaction. Both execution-layer flow control and the operator user-experience dimension are developed fully in Chapter 2 (Section 2.2 for execution-layer flow control; Section 2.7 for the operator user-experience dimension); they are introduced here because they define the boundaries of the research gaps that follow in Section 1.3.3.

1.3.3 Research Gap

The research problem emerges from the intersection of three persistent deficiencies in airport operations literature and practice.

Gap 1: Absence of field-validated evidence on execution-layer flow control.

While queueing theory and simulation studies have long identified passenger-flow variability as the primary driver of boarding-phase delays, empirical evidence on whether real-time, rule-based flow control can measurably stabilise these dynamics under authentic operational conditions remains absent (Schultz, 2018; Moreira et al., 2023). Existing boarding research relies predominantly on laboratory experiments, agent-based simulations, or controlled trials that impose idealised assumptions about passenger behaviour, gate architecture, and coordination protocols, conditions that rarely hold in live hub operations where architectural complexity, mixed passenger streams, shared-access

tunnels, and peak-load volatility create operational heterogeneity that simulation models cannot fully capture (Steffen and Hotchkiss, 2012; Kobbaey and Bilquise, 2023; Ryd et al., 2024). Consequently, airports lack field-validated evidence on whether execution-layer automation can deliver the variance-reduction benefits predicted by queueing-theoretic models when deployed at scale across diverse gate configurations and temporal regimes (Gehlen and Ronzani, 2025; Luo et al., 2022).

Gap 2: Prediction-execution disconnect in A-CDM frameworks.

A-CDM frameworks have successfully improved milestone coordination and predictive accuracy, yet these advances address symptoms rather than root causes (Eurocontrol, 2017; Okwir, Amouzgar and Ng, 2025; Tang et al., 2025). A-CDM systems predict when delays will occur and alert stakeholders to deviations, but they do not intervene in the upstream passenger-flow processes that generate those deviations. Process-mining analyses of A-CDM event logs reveal persistent data-quality issues, irregular milestone adherence, and coordination fragilities that undermine the reliability of Target Off-Block Time (TOBT) and Target Start-Up Approval Time (TSAT) assignments, indicating that prediction alone cannot stabilise turnarounds when the underlying flow dynamics remain uncontrolled (Rott, Schultz and Fricke, 2023; De Falco et al., 2023). The industry therefore requires execution-oriented technologies capable of acting on flow states in real time, capabilities that transcend the monitoring and prediction paradigm that currently dominates A-CDM implementations (Gehlen and Ronzani, 2025; Tang et al., 2025).

Gap 3: Underexamined operator user-experience dimension of flow-control automation.

The human-system integration dimension of real-time flow-control automation remains critically underexamined in airport operations research. While human-automation interaction studies in aviation have extensively documented the importance of how operators perceive system predictability, maintain accurate mental models, and calibrate their reliance on automated systems (Lee and See, 2004; Endsley, 2017; Parasuraman and Riley, 1997), these insights have not been systematically applied to gate-area flow-control technologies where frontline operators (gate agents, coordinators, supervisors, and security

personnel) execute the timing, sequencing, and coordination actions through which algorithmic recommendations are realised. Existing airport operations research focuses almost exclusively on process outcomes captured through sensor logs, discrete-event simulations, or archival data analysis, neglecting the user-experience, cognitive, and motivational mechanisms through which operators internalise system behaviour and translate stabilised flow into engagement, performance, and satisfaction (Schultz, 2018; Schultz and Fricke, 2011; Moreira et al., 2023). This omission is consequential because operator perceptions of system predictability, autonomy preservation, and performance contribution constitute primary determinants of whether digital interventions achieve sustained adoption and operational effectiveness in live gate environments (Bakker and Demerouti, 2007; DeLone and McLean, 2003; Venkatesh and Davis, 2000).

1.4 RESEARCH AIM AND OBJECTIVES

1.4.1 Research Aims

The aim of this research is to evaluate the operational impact and the operator user-experience mechanisms associated with the deployment of a real-time, rule-based passenger-flow control system in airport boarding operations, integrating queueing-theoretic and socio-technical perspectives. This aim addresses the need for both field-validated proof that execution-layer automation can reduce queue-sensitive turnaround variability under authentic operational conditions, and explanation of how frontline operators perceive, internalise, and respond to the resulting changes in flow predictability, task clarity, and workload rhythm. The aim is framed as an evaluation rather than a development or design exercise, because the rtBRMS technology has been independently developed and deployed in live operations at the study airport prior to this research; what is missing is rigorous empirical evidence on its operational effects and the operator user-experience mechanisms through which those effects are sustained. The researcher's role is therefore evaluative, not developmental. Importantly, the participants in Study 2 are active users of rtBRMS who utilise the system daily in their gate-operations work, so the constructs measured in Study 2 are post-use evaluations grounded in direct utilisation rather than abstract opinions formed without experience, in line with the experienced-user

assumption of the Technology Acceptance Model 2 (Venkatesh and Davis, 2000) and the post-acceptance framing of Bhattacherjee (2001).

This aim is achieved through a multi-method research design combining two complementary empirical investigations. Study 1 addresses the operational dimension through a 48-stratum field experiment across 171 live flights at Mashhad International Airport (MHD), providing high-resolution, audit-traceable evidence on how rule-based automation transforms turnaround efficiency under real-world heterogeneity. Study 2 addresses the operator user-experience dimension through a cross-sectional survey of 224 frontline operators analysed via Partial Least Squares Structural Equation Modelling (PLS-SEM), explaining the cognitive and motivational pathways through which operators convert perceived flow regulation into engagement, performance, productivity, and satisfaction. The integration of both studies in Chapter 6 demonstrates how operational variance reduction and operator user-experience acceptance jointly determine whether real-time flow-control systems achieve sustained effectiveness in live gate environments.

The research is bounded to short-haul turnaround operations at Mashhad International Airport (MHD), focusing on gate-area flow control. It does not examine long-haul operations, alternative boarding sequencing strategies, economic cost-benefit analysis, passenger-side perceptions, or integration with upstream and downstream terminal processes. These boundaries ensure methodological rigour and external validity within the defined scope.

1.4.2 Research Objectives

Three research objectives operationalise the aim. The research objectives of this study are:

RO1: To quantify the effect of rule-based flow-control automation on Gate Occupation Time, boarding and deboarding windows, throughput, and fast-process thresholds in live operations.

RO1 is addressed through Study 1, a quasi-experimental field study of 171 short-haul turnarounds at Mashhad International Airport stratified across 48 operational cells, tested

via hypotheses S1-H1 to S1-H6b. The hypothesis set covers aggregate Gate Occupation Time (S1-H1), boarding and deboarding windows (S1-H2a, S1-H2b), passenger throughput (S1-H3), architectural-complexity moderation (S1-H4), passenger-load and temporal robustness (S1-H5), and the binary fast-process thresholds for boarding ≤13 min and deboarding ≤11 min (S1-H6a, S1-H6b).

RO2: To examine how operators perceive flow stability and system predictability, and how these perceptions influence perceived performance contribution, engagement, individual work performance, productivity, and system satisfaction.

RO2 is addressed through Study 2, a cross-sectional survey of 224 frontline operators (gate agents, coordinators, supervisors, security personnel, ground handlers) analysed via PLS-SEM with 5,000 bootstrap resamples, tested via the seventeen direct-effect hypotheses S2-H1 to S2-H9b and the eight moderation hypotheses S2-H10 to S2-H17, examining the user-experience-motivational pathway from flow stability through predictability, contribution, and engagement to performance, productivity, and satisfaction, and the contextual conditions under which these relationships are strengthened or attenuated.

RO3: To integrate operational and operator user-experience evidence into a unified socio-technical explanation of how regulated flow translates into operator-level and system-level outcomes.

RO3 is addressed through the synthesis of Study 1 and Study 2 findings in Chapter 6.

1.4.3 Alignment of Objectives, Studies, and Hypotheses

Figure 1-1 presents the alignment of research objectives, empirical studies, and hypotheses, ensuring that every hypothesis is anchored in a specific research objective. RO1 is operationalised through Study 1, with six main hypotheses subdivided into eight directional tests (S1-H1, S1-H2a, S1-H2b, S1-H3, S1-H4, S1-H5, S1-H6a, S1-H6b) spanning aggregate performance, process windows, throughput, architectural moderation, load robustness, and binary KPIs. RO2 is operationalised through Study 2, with 25 hypothesis tests spanning the antecedent layer (S2-H1 to S2-H5b), the structural-cascade layer through the intervening constructs PSP, PPC, and ENG (S2-H6 to S2-H9b), and the

moderation layer (S2-H10 to S2-H17). RO3 is addressed through the integration of both studies, synthesised in Chapter 6.

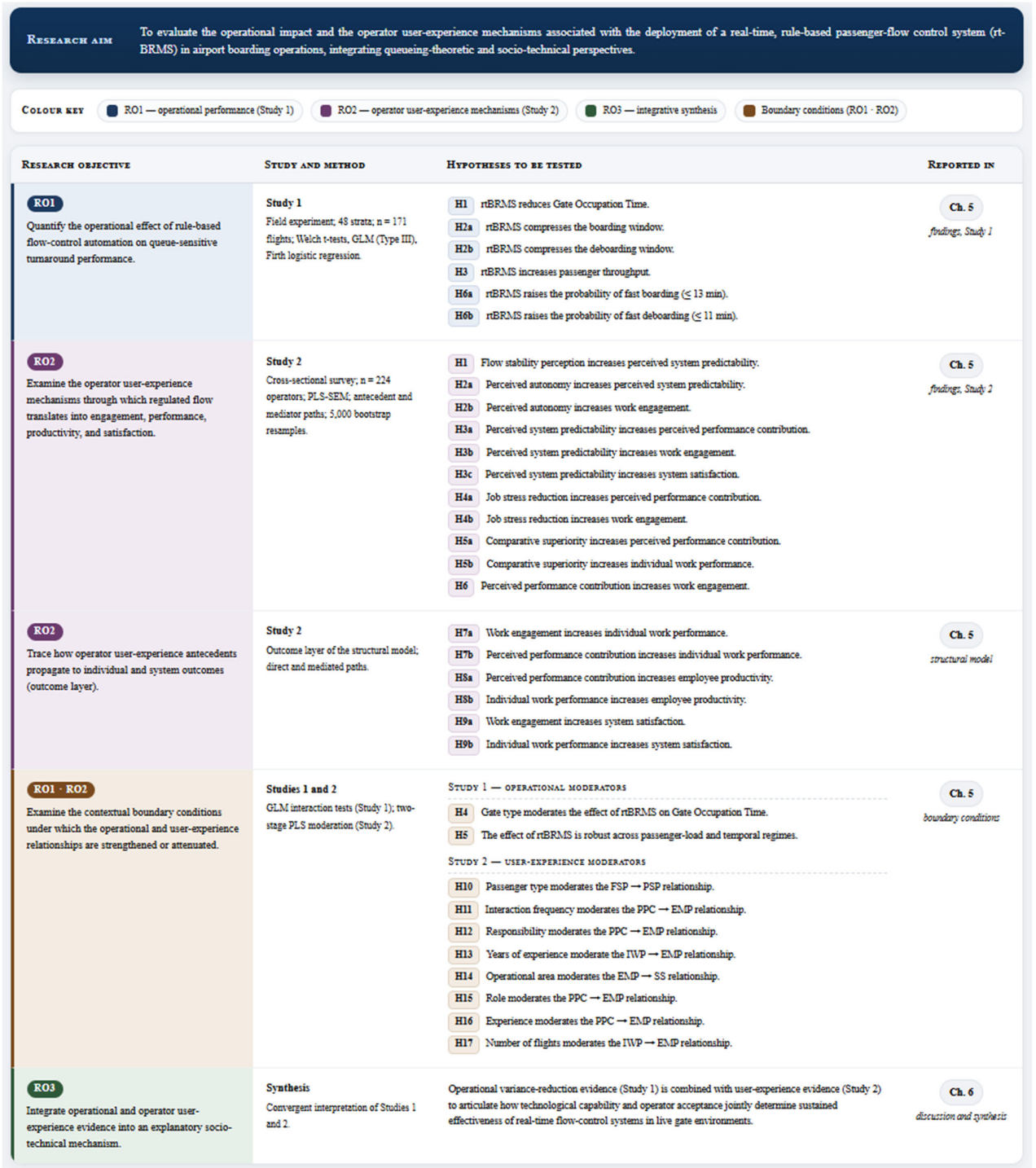


Figure 1-1 Alignment of Research Objectives, Studies, and Hypotheses

Note: Construct abbreviations (Study 2): FSP = Flow Stability Perception; PSP = Perceived System Predictability; AUT = Perceived Autonomy; JSR = Job Stress Reduction; CSR = Comparative Superiority; PPC = Perceived Performance Contribution; ENG = Work Engagement; IWP = Individual Work Performance; EMP = Employee Productivity; SS = System Satisfaction.

1.5 ANTICIPATED CONTRIBUTIONS TO THEORY AND PRACTICE

Against the gaps that Chapter 2 will identify in the operational, human-factors, and socio-technical streams of the rtBRMS literature, this thesis aims to deliver five theoretical contributions, plus five practical contributions, the realised form of which is reported in Section 7.3 and 7.4. Each contribution is positioned at one of the boundaries that has historically separated the disciplines this thesis bridges — operational research from organisational behaviour, simulation evidence from field evidence, and prediction from execution.

First, a methodological contribution. The thesis aims to deliver a replicable two-lens evaluation protocol for socio-technical interventions, in which an operational study (quasi-experimental field design with stratified covariate adjustment) and an operator user-experience study (cross-sectional PLS-SEM) are sequenced so that the operational change measured in the first study provides the empirical warrant for interpreting the user-experience change measured in the second. This protocol is intended to be transferable to other socio-technical evaluations in aviation (A-CDM implementations, remote tower operations, automated ground handling) and beyond.

Second, a theoretical contribution to airport operations and turnaround management. The thesis aims to extend the airport-operations literature, which has been dominated by simulation studies of boarding strategies and monitoring-centric A-CDM evaluations, by providing field-causal evidence that variance suppression at the door–tunnel–aisle interface is the operative antecedent of reliable turnarounds. The theoretical claim is that the relationship between flow control and milestone reliability is mechanistic rather than merely correlational, and that this mechanism follows the logic of Little's law and Kingman's heavy-traffic approximation.

Third, a theoretical contribution to human–automation teaming in airport contexts. The thesis aims to provide a mechanistic account of how stabilised passenger flow is internalised by operators as predictability, how predictability underwrites usefulness beliefs, and how usefulness and engagement together drive execution and productivity. The theoretical claim is that the psychological states that the human–automation literature has long identified as essential for sustained automation use (predictability, perceived usefulness, engagement) can be systematically produced by a physical flow-control mechanism, rather than treated as exogenous traits of the operator population.

Fourth, a contribution to professional practice. The thesis aims to translate the first three contributions into a set of evidence-based design rules covering deployment prioritisation, human–machine interface design, decision-rights allocation, and change management for execution-layer automation in multi-organisational gate environments. The practical claim is that these rules can be derived directly from path coefficients, and effect sizes rather than from generic recommendations to "adopt digital tools".

Taken together, these four contributions frame rtBRMS effectiveness as a joint property of the technical mechanism, the operators who enact it, and the organisational context in which it is deployed. They motivate the dual-study design described in Chapter 3 and are revisited, in their realised form and with empirical claims attached, in Section 7.4. The remainder of this chapter sets out the structure of the thesis (Section 1.6) and closes with a chapter summary (Section 1.7).

1.6 STRUCTURE OF THE THESIS

This thesis is organised into six chapters that systematically develop the theoretical foundation, empirical evidence, and practical implications of real-time, rule-based passenger-flow control in airport operations. Figure 1-2 presents the thesis structure roadmap, mapping the six-chapter architecture: Chapter 1 frames the problem and research objectives; Chapter 2 develops the theoretical foundations and hypotheses; Chapter 3 specifies the methodological architecture; Chapter 4 documents the methods and procedures for both studies; Chapter 5 reports the findings; and Chapter 6 integrates and

discusses the evidence. Each chapter feeds the next, with explicit return loops where Chapter 6 traces findings back to the research objectives and hypotheses defined in Chapter 1.

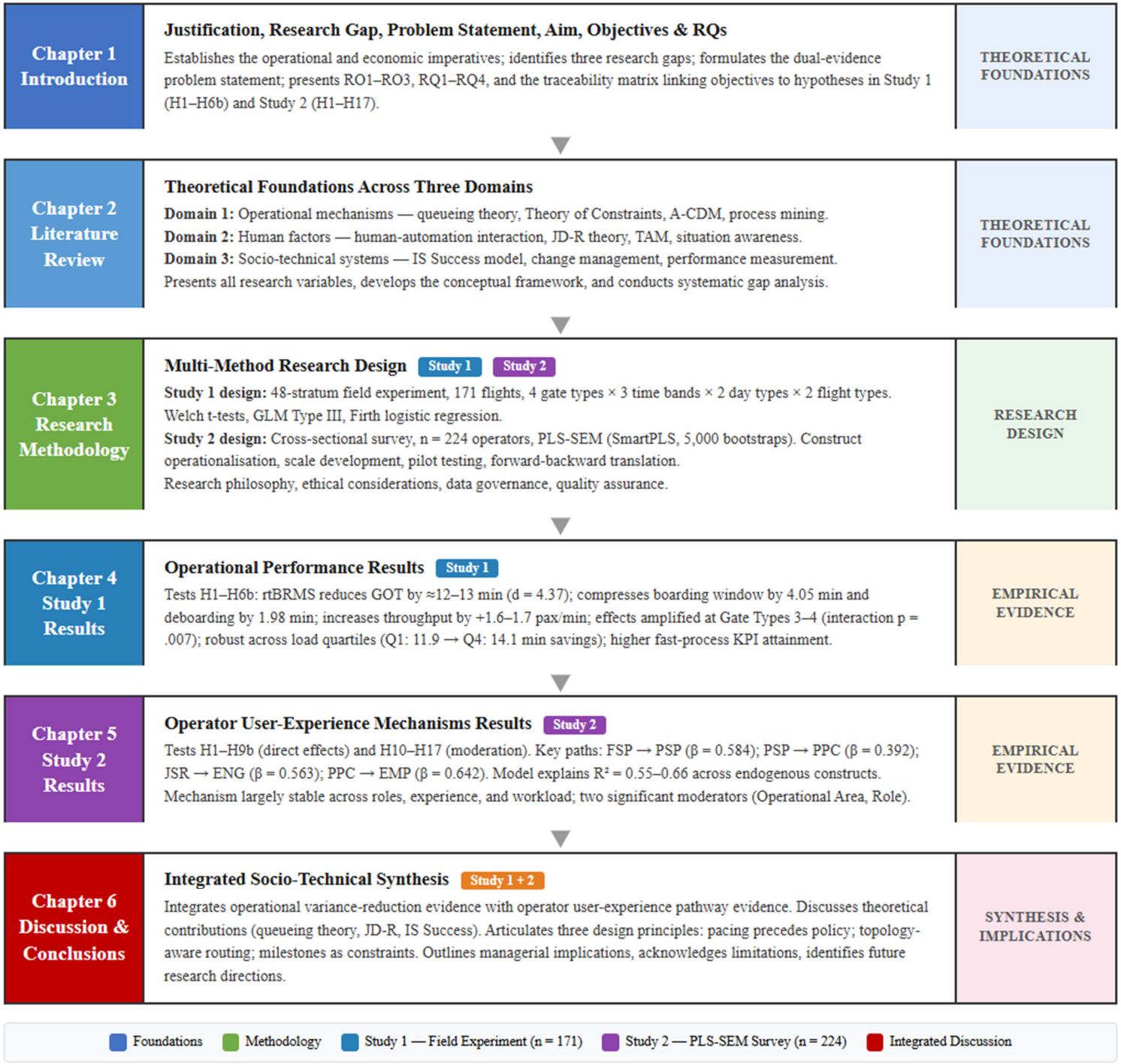


Figure 1-2 Thesis Structure Roadmap

Chapter 1 (Introduction) has established the rationale for this research by demonstrating the convergence of accelerating passenger demand, infrastructure constraints, and the limitations of prediction-oriented A-CDM frameworks. The dual-evidence requirement, namely operational proof of variance reduction together with explanation of how operators convert system predictability into engagement, performance, and satisfaction, was operationalised through three research objectives and a traceability matrix linking every hypothesis in Study 1.

Chapter 2 (Literature Review) develops the theoretical foundations across three interconnected domains: operational mechanisms and digital technologies (queueing theory, Theory of Constraints, A-CDM frameworks, process mining), human factors and work organisation (human-automation interaction, Job Demands-Resources theory, Technology Acceptance Model, situation awareness), and socio-technical systems and implementation (Information Systems Success model, change management, performance measurement). The chapter presents all research variables, discusses the theories underpinning both studies, and concludes with a systematic gap analysis and the conceptual framework that guides the empirical investigations.

Chapter 3 (Research Methodology) provides comprehensive documentation of the research design, data collection procedures, measurement instruments, and analytical strategies for both the 48-stratum field experiment (Study 1) and the cross-sectional operator-perception survey (Study 2). Ethical considerations, data governance, and quality assurance protocols are also addressed.

Chapter 4 (DATA ANALYSIS AND MEASUREMENT VALIDATION) reports the detailed methodological implementation of both studies, including the data acquisition and reconciliation pipeline for Study 1 and the instrument development, translation, and PLS-SEM evaluation framework for Study 2.

Chapter 5 (Findings of the Study) reports empirical findings from both studies. The operational results test hypotheses S1-H1 – S1-H6b examining rtBRMS effects across

171 flights and 48 operational strata. The operator user-experience results test 17 direct-effect hypotheses and 8 moderation hypotheses tracing the user-experience-motivational cascade from flow stability perception to individual work performance, employee productivity, and system satisfaction.

Chapter 6 (Discussion) integrates findings from both studies, demonstrating how operational variance reduction and operator user-experience acceptance jointly determine the effectiveness of real-time flow-control systems in live gate environments, and discusses how the evidence advances queueing-theoretic, human-automation, and information-systems frameworks.

Chapter 7 (Conclusion) consolidates the theoretical and practical contributions, outlines managerial and policy implications, acknowledges limitations, identifies directions for future research, and closes with reflexive observations on the doctoral journey.

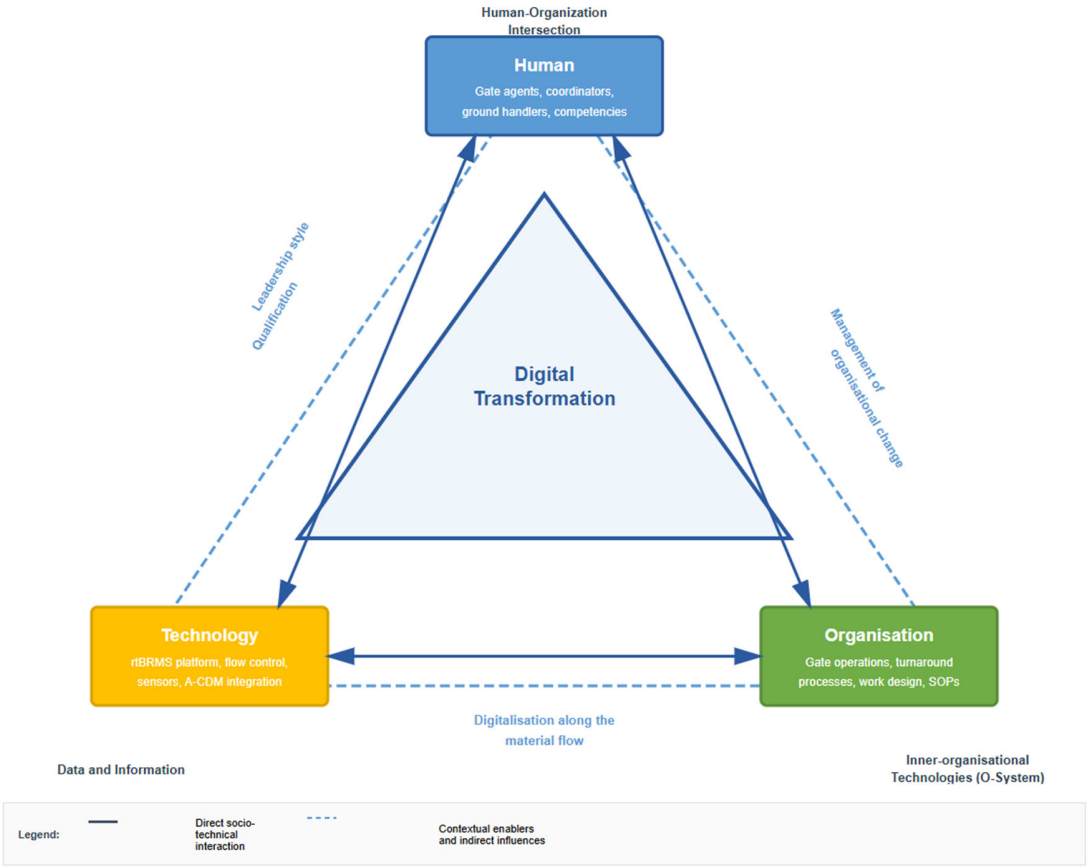


Figure 1-3 Socio-technical Triangle of Digital Transformation – A Framework for rtBRMS (Adapted from Bostrom and Heinen, 1977; Clegg, 2000).

Figure 1.3 illustrates the socio-technical triangle framework adapted for rtBRMS implementation in airport operations. The framework identifies three core components that must be jointly optimized for successful digital transformation: Technology (rtBRMS platform, flow-control algorithms, sensors, A-CDM integration), Organization (gate operations, turnaround processes, work design, standard operating procedures), and Human (gate agents, coordinators, ground handlers, competencies). Two distinct line styles are used to capture two different kinds of relationship in the framework, and the distinction is central to the way the model is read.

The solid bidirectional arrows that connect the three vertices and pass through the central "Digital Transformation" zone represent direct socio-technical interactions: the

reciprocal influences between Technology, Organization, and Human that constitute the day-to-day operating reality of the gate. A change in any one vertex propagates immediately into the other two through these solid links, which is why successful digital transformation requires joint optimization rather than independent optimization of any single component (Bostrom and Heinen, 1977; Clegg, 2000).

The dashed arrows on the outer edges of the triangle represent contextual enablers and indirect influences: factors that are not themselves part of the day-to-day socio-technical interaction but that condition whether and how that interaction can occur. Three such enablers are shown explicitly. Leadership style and qualification (dashed arrow from Human to Technology) conditions how operators acquire and apply the technical competence needed to use rtBRMS effectively, but is itself a property of the wider organizational environment rather than of the operator–system interaction at the gate. Management of organizational change (dashed arrow from Human to Organization) conditions whether the new work design that rtBRMS implies is accepted, internalized, and sustained, but again sits one level above the operator–task interaction itself. Digitalization along the material flow (dashed arrow from Technology to Organization) conditions the data-quality and integration substrate on which rtBRMS depends but which the rtBRMS system itself does not produce. The dashed style therefore communicates that these three influences are necessary preconditions for the solid socio-technical interactions to function, without being part of those interactions.

solid-versus-dashed distinction underpins the multi-method design of this thesis. Study 1 measures the direct socio-technical interactions at the operational level (the solid links), specifically the consequences for Gate Occupation Time, boarding and deboarding windows, and throughput when rtBRMS is active in the Technology vertex. Study 2 measures how operators internalize those changes and translate them into engagement, performance, and satisfaction, that is, the human side of the same solid links. The dashed contextual enablers (leadership, change management, infrastructure digitalization) are not directly measured but are explicitly acknowledged as boundary conditions in Section 7.4 and recognized as priorities for further research. The figure therefore performs two jobs at

once: it shows what this thesis evaluates (the solid interactions) and what it bounds out as context (the dashed enablers), and the two line styles must be read together for the framework to make sense.

1.7 CHAPTER SUMMARY

This chapter set out the justification, research gap, and conceptual architecture guiding the two empirical studies. Accelerating global passenger demand (IATA, 2026: 5.3% year-on-year growth, 83.6% load factors), persistent infrastructure constraints, and boarding-phase delays exceeding 10 minutes in 15 to 25% of short-haul operations at major European hubs (Eurocontrol Performance Review Unit, 2022; Fricke and Schultz, 2009), generating annual delay costs exceeding €5 billion across European networks (Cook et al., 2021), elevate gate-level turnaround performance to a strategic imperative. A-CDM frameworks and predictive analytics improve milestone visibility but do not regulate the upstream passenger-flow processes that generate variability at gates, creating a prediction-execution gap.

Three research gaps were identified: the absence of field-validated evidence on real-time flow control under authentic conditions; the prediction-execution disconnect in current A-CDM technologies; and the underexamined operator user-experience dimension of gate-area automation. The dual-evidence requirement, namely operational proof of variance reduction together with explanation of how operators convert system predictability into engagement, performance, and satisfaction, was operationalised through three research objectives, and a traceability matrix linking every hypothesis in Study 1 (S1-H1 to S1-H6b) and Study 2 (S2-H1 to S2-H9b for direct effects and S2-H10 to S2-H17 for moderations) to its corresponding objective. The multi-method design (171-flight, 48-stratum field experiment at Mashhad International Airport analysed via Welch t-tests, Type III General Linear Models, and Firth-penalised logistic regression for binary fast-process KPIs; 224-respondent cross-sectional PLS-SEM survey with 5,000 bootstrap resamples) is bounded to short-haul operations under A-CDM protocols, excluding long-haul operations, alternative boarding sequencing strategies, economic cost-benefit analysis, and passenger-

side perceptions. Chapter 2 develops the theoretical foundations across the three domains identified.

2. LITERATURE REVIEW

2.1 OVERVIEW OF THE CHAPTER

This chapter synthesises the theoretical and empirical foundations for evaluating real-time, rule-based passenger-flow control across three interconnected domains: operational mechanisms (Study 1), human factors (Study 2), and socio-technical implementation (cross-study). A narrative review is adopted because systematic-review protocols cannot integrate boarding-interference studies, A-CDM governance, motivational theories, and operator-acceptance research within a single discipline (Bolderston, 2008; Ferrari, 2015); the relevance tree (Figure 2.1) sets boundaries and excludes peripheral literatures (Hart, 2018). Sections 2.1–2.6 develop the operational foundations; Section 2.7 presents the four human-factor frameworks (JD-R, TAM2, Human-Automation Interaction, IS Success); Sections 2.8–2.11 derive the conceptual framework and formal hypotheses; Section 2.12 closes the chapter.

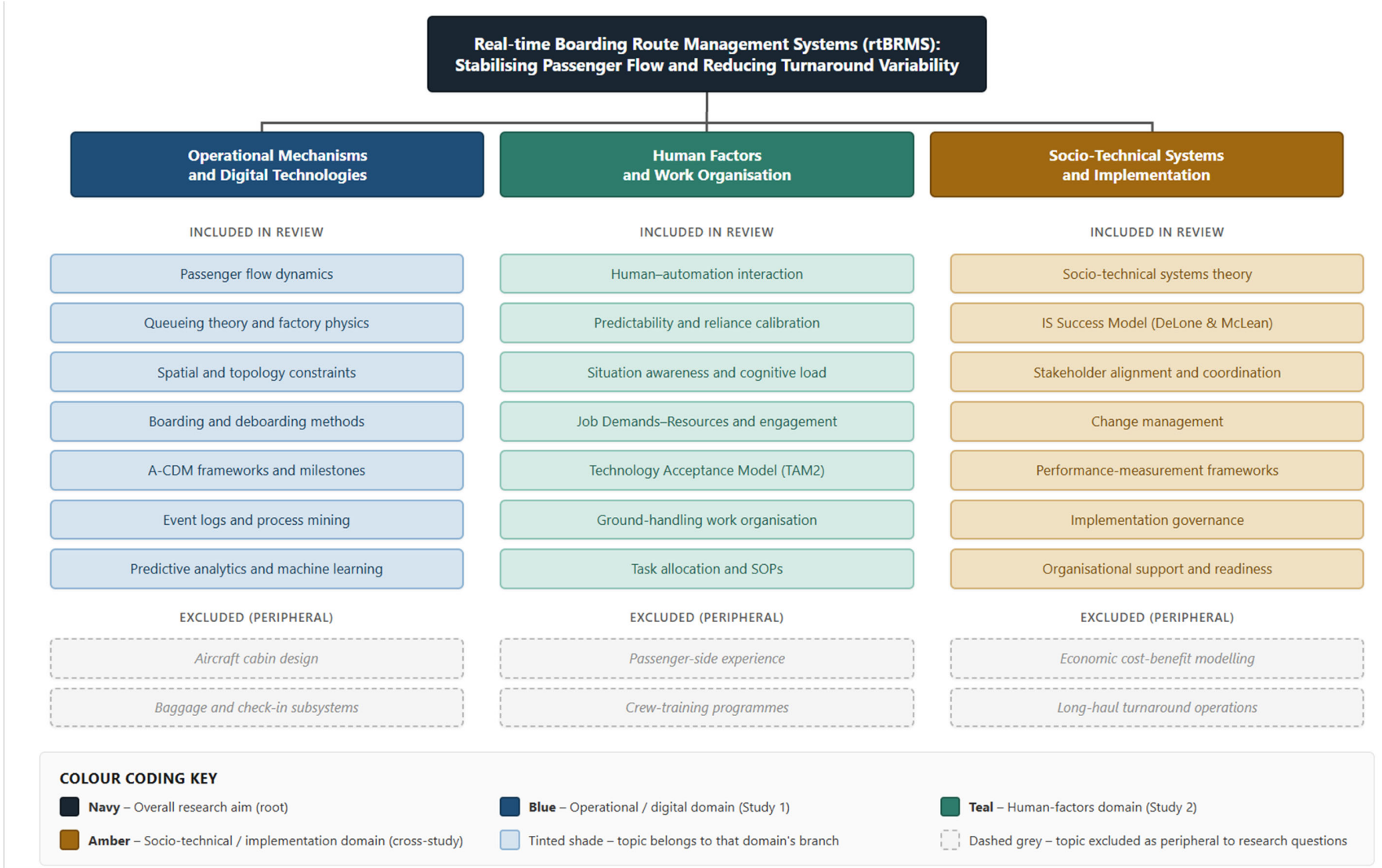
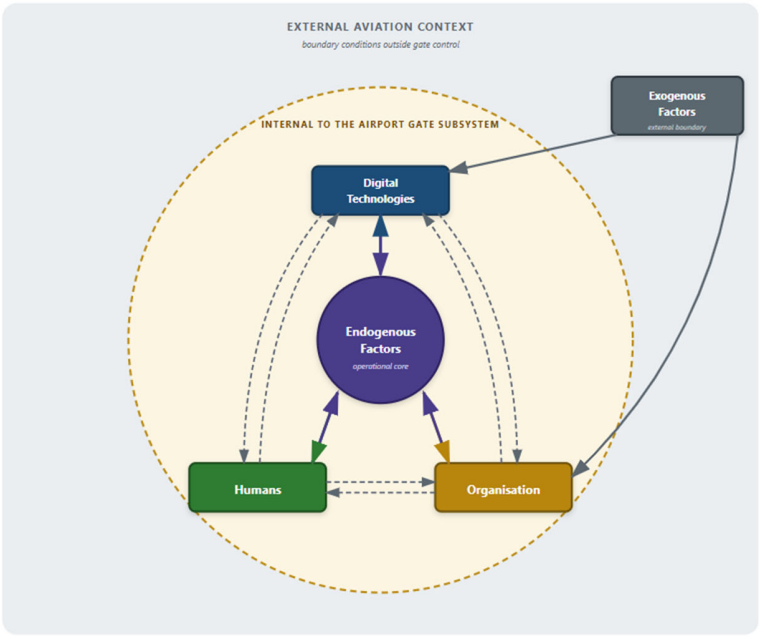


Figure 2-1 Relevance Tree for Literature Review - Hierarchical decomposition of the rtBRMS research domain into three theoretical domains and their constituent topics

Colour-coding rationale. Three saturated hues (blue, teal, amber) are assigned one-to-one to the three primary research domains and are reused throughout Chapter 2 (Figures 2.5–2.9, Table 2.1) so that any topic, framework, or domain-of-impact figure can be visually traced back to its parent domain. Each domain header uses the saturated hue; child topics use a desaturated tint of the same hue, preserving the visual lineage between branch and root. The dark-navy root denotes the overall thesis aim that subsumes all three branches. Excluded peripheral topics use neutral grey with a dashed border to visually separate scope-out items from in-scope literature. The same color mapping anchors the dual-study design: blue = Study 1 (operational), teal = Study 2 (operator user-experience), amber = the cross-study socio-technical implementation context.

The literature review is therefore structured based on the narrowing down of the literature through the methodology of the relevance tree and the findings on research around real-time boarding route management systems (rtBRMS) and airport operational transformation from this section, leading to the conceptual framework shown in Figure 2.2, where the "Determinants of rtBRMS Implementation and Effectiveness in Airport Operations" are presented. Table 2.1 outlines the sub-areas of the components of the framework which are considered in the literature review and addressed in subsequent sections.



SPATIAL ZONES

Where a determinant is positioned in the diagram tells you whether the gate operator can act on it directly.

Cream circle = inside the gate subsystem (operator-controllable)

Grey field = outside the gate subsystem (boundary conditions)

DETERMINANT CATEGORIES

Each colour identifies one determinant category. Saturated fill = the determinant itself; the same colour on its arrow = its bidirectional link to the operational core.

Purple — Endogenous Factors (operational core)

Operational mechanisms and queueing theory · passenger flow dynamics · gate architecture and spatial constraints · turnaround process characteristics.

Role: the operational substrate that all other determinants act upon and react to.

→ Sub-sections 2.3.2, 2.3.3

Blue — Digital Technologies

Real-time flow control · A-CDM integration · event-log systems and process mining · predictive analytics and machine learning.

Role: the technical layer that exerts real-time control over the operational core.

→ Section 2.4

Green — Humans

Human–automation interaction · predictability calibration and mental models · operator competencies and training · work engagement and motivation · perceived predictability and autonomy.

Role: the actor layer whose perceptions and behaviour translate prescribed sequences into reliable execution.

→ Section 2.5 / Sub-section 2.5.4

Amber — Organisation

Ground-handling work organisation · task allocation and coordination mechanisms · standard operating procedures (SOPs) · socio-technical system design · change management and implementation.

Role: the work-organisational layer through which technology and humans are jointly enacted.

→ Sub-sections 2.5.1, 2.5.2 / Section 2.5

Grey — Exogenous Factors (external boundary)

Airport infrastructure constraints · airline operational demands · regulatory requirements and safety standards · network punctuality pressures.

Role: boundary conditions that

act on

the gate subsystem but cannot be controlled from within it; therefore depicted with one-way arrows crossing into the cream zone.

→ Sub-section 2.5.3

Figure 2-2 Determinants of rtBRMS Implementation and Effectiveness - Five interacting determinant categories arranged around the operational core of the airport gate subsystem (Adapted from Foerster-Metz et al. (2018)).

As such, the areas to be considered are highlighted in the course of the literature review, where they are complemented and delineated by relevant current research in airport operations, queueing theory, human-automation interaction, and socio-technical systems implementation.

Figure 2.2 is adapted from the digital-transformation determinants framework of Foerster-Metz et al. (2018) and re-specified for the airport gate-operations context of this thesis. The framework distinguishes five determinant categories that jointly shape whether a real-time boarding route management system (rtBRMS) can be implemented successfully and whether, once implemented, it delivers measurable operational effect. Digital Technologies denotes the technical means by which rtBRMS exerts real-time control over the boarding sequence, including rule-based flow-control logic, Airport Collaborative Decision Making (A-CDM) integration, event-log capture and process mining, and predictive analytics. Endogenous Factors denote the operational characteristics internal to the gate subsystem itself: the queueing dynamics of passenger flow, the spatial topology of the gate, the geometry of the boarding bridge or apron route, and the temporal structure of the turnaround process. These factors set the physical and process-level boundary conditions within which rtBRMS must act. Exogenous Factors denote the external aviation context that the gate cannot control but must respond to, including airport-wide infrastructure constraints, airline operational demands, regulatory and safety requirements, and the punctuality pressure carried from the wider air-traffic network. Organisation denotes the work-organisational arrangements through which the technology is enacted in practice, including ground-handling work design, task allocation and coordination mechanisms among gate agents, standard operating procedures, the socio-technical fit between the rule-engine and the human role, and the change-management activities that accompany roll-out. Humans denotes the operator-level conditions that determine whether automation is accepted and used as intended, including human–automation interaction, the calibration of operators' mental models to the system's behaviour, operator competencies and training, work engagement and motivation, and perceived predictability and autonomy at the gate. The five categories are not independent: digital technologies and endogenous factors define what rtBRMS can compute and execute; exogenous factors define the

demand and constraint envelope it must respect; and the organisation and humans categories together determine whether the system's prescribed sequence is converted into reliable on-the-ground action. Effectiveness, in this framework, is therefore a joint property of all five determinants rather than the property of the technology alone, which is why the literature review in subsequent sections addresses each category in turn before integrating them in the conceptual framework that closes the chapter.

Component	Sub-Areas	Section/Sub-section
Digital Technologies	- Real-time flow control systems - Airport Collaborative Decision Making (A-CDM) - Event-log systems and process mining - Predictive analytics and machine learning	Section 2.4
Endogenous Factors	- Operational mechanisms and queueing theory - Passenger flow dynamics - Gate architecture and spatial constraints - Turnaround process characteristics	Sub-section 2.3.2 Sub-section 2.3.3
Exogenous Factors	- Airport infrastructure constraints - Airline operational demands - Regulatory requirements and safety standards - Network punctuality pressures	Sub-section 2.5.3
Organisation	- Ground handling work organization - Task allocation and coordination mechanisms - Standard operating procedures (SOPs) - Socio-technical system design - Change management and implementation	Sub-section 2.5.1 Sub-section 2.5.2 Section 2.5
Humans	- Human-automation interaction - Predictability calibration and mental models - Operator competencies and training - Work engagement and motivation - Perceived predictability and autonomy	Section 2.5 Sub-section 2.5.4

Table 2-1 Sections and areas of determinants for rtBRMS implementation and effectiveness.

This Table provides a roadmap linking each determinant category to specific sub areas and corresponding sections of the chapter. This ensures that the literature review is systematically structured, transparent in its logic, and aligned with the conceptual and empirical aims of the thesis.

2.1.1 Literature Search Strategy and Critical Approach

Literature was collected through a systematic search combining electronic database searching, citation tracking, and practitioner-source monitoring, consistent with the integrative-review approach for multidisciplinary problems (Torraco, 2005; Snyder, 2019). Searches were conducted across Scopus (engineering, operations research, transportation), Web of Science (organisational behaviour, psychology, IS), and Google Scholar (conference proceedings, working papers, institutional reports). Boolean keywords aligned with the three relevance-tree domains: operational mechanisms ("passenger boarding" AND "queueing theory" / "turnaround" / "gate operations" / "flow control" / "boarding strategy"); human factors ("human-automation interaction" AND "predictability" / "engagement" / "work performance" / "technology acceptance" AND "aviation" / "airport"); and socio-technical integration ("socio-technical" AND "airport" / "ground handling" / "digital transformation" / "change management"). Targeted searches covered specific frameworks ("Job Demands-Resources" AND "performance"; "PLS-SEM" AND "airport"; "IS success model" AND "operational systems").

Coverage spanned 2000 to 2025, capturing the maturation of A-CDM frameworks across European hubs (Eurocontrol, 2017), the establishment of PLS-SEM as a rigorous methodology in management research (Hair et al., 2019), and the emergence of real-time flow-control technologies and process-mining applications in turnaround management from 2018 onwards (Rott, Schultz and Fricke, 2023; Okwir, Amouzgar and Ng, 2025). Foundational pre-2000 works were retained where they established core frameworks: queueing theory (Kingman, 1961; Little, 1961), socio-technical systems theory (Trist and Bamforth, 1951), Theory of Constraints (Goldratt, 1984), and factory physics (Hopp and

Spearman, 2011). Inclusion required peer-reviewed journal articles, recognised conference proceedings (ATRS, TRB, SESAR Innovation Days), or authoritative institutional reports (Eurocontrol, IATA, ICAO). Backward and forward citation tracking on seminal works (Schultz, 2018; Halpern and Mwesiumo, 2021; Lee and See, 2004; Bakker and Demerouti, 2007; DeLone and McLean, 2003; Venkatesh and Davis, 2000) was applied until theoretical saturation, yielding a corpus of approximately 250 sources.

The review is critically analytical rather than descriptive (Hart, 2018; Ridley, 2012), evaluating methodological rigour, identifying contradictions across research streams, and assessing how far existing evidence addresses real-time gate-level flow control. Three recurring limitations recur throughout. First, the airport operations literature relies overwhelmingly on simulation-based evidence and observational comparisons rather than controlled field experiments, limiting causal claims (Schultz, 2018; Moreira et al., 2023). Second, A-CDM and predictive-analytics evaluations report aggregate improvements without isolating gate-level effects or controlling for confounders, creating attribution uncertainties that are addressed here through the 48-stratum field design (SESAR Joint Undertaking, 2016; Guo et al., 2020). Third, process-mining and human-factors literatures operate in disciplinary silos: process-mining researchers document variability without examining operator experience, while human-factors researchers study acceptance without grounding models in specific operational processes; this fragmentation is bridged by the integrated dual-study design.

2.1.2 Integration with Research Framework

The five-determinant framework introduced in Figure 2.2 is not a free-standing typology; it is the structural bridge that links the literature reviewed in this chapter to the empirical investigation reported in Chapters 4 and 5. Each of the five determinants, Digital Technologies, Endogenous Factors, Exogenous Factors, Organisation, and Humans, maps onto one of the three perspectives that constitute the dual-study research framework introduced in Chapter 1. The mapping is one-directional and explicit: every hypothesis tested in this thesis can be traced back to the determinant from which its theoretical justification is drawn, and every determinant is operationalised through at least one

measured construct or covariate. This subsection makes the mapping explicit so that the reader can read the literature review (this chapter), the methodology (Chapter 3), and the empirical chapters (Chapters 4 and 5) as a single coherent argument rather than three separate documents.

Operational performance perspective (Study 1)

The first perspective addresses how rtBRMS technically reduces variance in queue-sensitive turnaround performance, and it is operationalised by Study 1, the 48-stratum quasi-experimental field study of 171 flights at Mashhad International Airport. Two of the five determinants feed directly into this perspective. Digital Technologies, the rule-based flow controller, A-CDM integration, event-log capture, and predictive analytics described in Section 2.4, supplies the technical means by which rtBRMS exerts real-time control over passenger flow at the gate. Endogenous Factors, the operational mechanisms and queueing dynamics, passenger-flow characteristics, gate architecture, and turnaround-process structure described in Section 2.3.2 and Section 2.3.3, supply the physical and process-level boundary conditions on which that control acts. The mechanistic prediction that follows is a queueing-theoretic one: variance suppression at the door–tunnel–aisle interface should compress process windows and stabilise milestones (Kingman, 1961; Little, 1961; Hopp and Spearman, 2011). This prediction is converted into the eight directional tests S1-H1 to S1-H6b under RO1, which examine the rtBRMS effect on Gate Occupation Time, boarding and deboarding windows, throughput, the architectural-complexity moderation, the load-robustness moderation, and the FastBoard / FastDeboard binary KPIs.

Operator User-Experience Mechanisms Perspective (Study 2)

The second perspective addresses how operators perceive, internalise, and respond to the stabilised flow that rtBRMS produces, and it is operationalised by Study 2, the cross-sectional PLS-SEM survey of 224 frontline operators. Only one of the five determinants feeds directly into this perspective: the Humans determinant, which encompasses human–automation interaction, predictability calibration, perceived autonomy, work engagement and motivation, and operator competencies (Lee and See, 2004; Bakker and Demerouti, 2007; Venkatesh and Davis, 2000; DeLone and McLean, 2003). The mechanistic

prediction here is psychological rather than queueing-theoretic: stabilised flow becomes perceived predictability, predictability underwrites perceived performance contribution and work engagement, and these in turn drive individual work performance, employee productivity, and system satisfaction. The Humans determinant is therefore operationalised through ten reflective and formative constructs (Flow Stability Perception, Perceived System Predictability, Perceived Autonomy, Job Stress Reduction, Comparative Superiority, Perceived Performance Contribution, Work Engagement, Individual Work Performance, Employee Productivity, System Satisfaction), and the mechanism is tested under RO2 through the seventeen direct-effect hypotheses S2-H1 to S2-H9b and the eight moderation hypotheses S2-H10 to S2-H17.

Implementation context (cross-study). The third perspective addresses the conditions under which the operational and operator user-experience mechanisms manifest, and it is operationalised across both studies rather than belonging to either alone. The remaining two determinants feed into this perspective. Organisation, ground-handling work design, task allocation, standard operating procedures, socio-technical system fit, and change management (Section 2.5.1, Section 2.5.2, Section 2.5), describes the work-organisational arrangements through which the technology is enacted in practice. Exogenous Factors, airport infrastructure constraints, airline operational demands, regulatory and safety requirements, and network punctuality pressures (Section 2.5.3), describes the external aviation context that constrains implementation but cannot be controlled at the gate. These two determinants do not generate stand-alone hypotheses of their own; instead, they are operationalised through the stratification dimensions and contextual moderators that condition the strength of the operational and operator user-experience mechanisms. In Study 1, under RO1, they appear as the four stratification dimensions of the 48-stratum design (gate topology, temporal period, day type, flight type) and as the moderation hypotheses S1-H4 (architectural complexity) and S1-H5 (passenger load and temporal regime). In Study 2, under RO2, they appear as the eight contextual moderators (passenger type, interaction frequency, level of responsibility, years of experience, operational area, role, and flights per shift) tested in S2-H10 to S2-H17. Cross-study integration under RO3 is addressed in Chapter 6.

Coherence across the thesis. The five-determinant framework therefore performs three connected jobs at once. It organises the literature reviewed in Section 2.2 to Section 2.7 around a single conceptual structure; it specifies which determinants are operationalised in which study and through which constructs; and it makes the boundary between mechanism (Studies 1 and 2) and context (the moderators and stratification dimensions) explicit, so the reader can see at a glance which findings to expect under what conditions. Table 2.2 lists the canonical theoretical foundation for each of the five determinants, providing the literature anchor against which the operational and operator user-experience mechanisms reviewed in subsequent sections should be read.

Component	Key Theoretical Foundations
Digital Technologies	Airport Collaborative Decision Making (Eurocontrol, 2017) · process mining (van der Aalst, 2016) · predictive analytics for turnaround operations (Guo et al., 2020; Okwir, Amouzgar and Ng, 2025) · real-time information systems in airport operations (Lee and Yu, 2018)
Endogenous Factors	Queueing theory and heavy-traffic approximation (Kingman, 1961; Whitt, 1993) · Little's Law (Little, 1961) · Theory of Constraints (Goldratt, 1984; Goldratt and Cox, 2004) · factory physics and variability propagation in serial systems (Hopp and Spearman, 2011)
Exogenous Factors	Airport capacity and infrastructure constraints (ICAO, 2018) · network punctuality and delay propagation (Eurocontrol, 2019; Pyrgiotis, Malone and Odoni, 2013) · regulatory and safety frameworks (EASA and FAA standards)
Organisation	Socio-technical systems theory (Trist and Bamforth, 1951; Mumford, 2006; Clegg, 2000) · change management (Kotter, 1996) · coordination mechanisms (Malone and Crowston, 1994) · ground-handling work organisation (Schultz and Fricke, 2011; Evler et al., 2022)
Humans	Human–automation interaction (Lee and See, 2004; Parasuraman and Riley, 1997; Endsley, 2017) · Job Demands–Resources theory (Bakker and Demerouti, 2007) · Technology Acceptance Model 2 (Venkatesh

Component	Key Theoretical Foundations
	and Davis, 2000) · Information Systems Success Model (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008)

Table 2-2 Theoretical Foundations by Component

2.2 OPERATIONAL TRANSFORMATION AT THE GATE: DEFINING THE DOMAIN

Section 1.3.1 distinguished three levels of digital intervention: digitisation (analogue to digital records), digitalisation (real-time information systems and predictive analytics), and execution control (systems that act on flow states in real time). This distinction is rarely made explicit in the airport-operations literature, where authors frequently conflate digitalisation with execution control, treating predictive dashboards and real-time flow regulation as equivalent forms of digital transformation (Halpern and Mwesiumo, 2021). Lee and Yu (2018) characterise real-time information systems as transformative without distinguishing systems that enhance visibility from systems that actively modulate flow; the SESAR Joint Undertaking (2016) likewise groups A-CDM milestone sharing and automated gate management under a single "digital performance" umbrella, obscuring the difference between observing a delay and preventing one. The conflation has practical consequences: studies that evaluate "digital transformation" without specifying whether the intervention involves monitoring, prediction, or execution control cannot isolate the causal mechanisms through which technology affects performance, leaving practitioners without guidance on which type of investment delivers the greatest return (Gehlen and Ronzani, 2025). This thesis addresses that gap by focusing on execution control, the least studied of the three levels, using a quasi-experimental field design that isolates the effect of real-time flow regulation from the monitoring and prediction capabilities already in place at the study airport.

2.2.1 Execution Control and the Variability-Sensitive Turnaround in Airport Contexts

Execution control at the gate rests on three integrated capabilities. Inflow pacing regulates the rate at which passengers are released from holding areas into downstream processes, preventing bursts that exceed spatial handling capacity (Steffen and Hotchkiss,

2012); Kingman's formula shows that controlling interarrival variance directly reduces waiting and cycle-time variability (Kingman, 1961), as validated in manufacturing (Hopp and Spearman, 2011; Buzacott and Shanthikumar, 1993) and service operations (Whitt, 1993; Kleinrock, 1975), with boarding simulations under controlled release achieving 20 to 30% reductions in boarding duration relative to uncontrolled batch release (Schultz, 2018; Jaehn and Neumann, 2015). Topology-aware routing extends pacing by accounting for gate architecture and shared-access geometries where multiple aircraft share corridors and simultaneous boarding/deboarding compete for capacity (Moreira et al., 2023; Tang et al., 2025); routing algorithms assigning passengers to specific doors based on real-time occupancy, drawing on robust optimisation (Bertsimas and Sim, 2004) and network flow theory, achieve 30 to 40% reductions in corridor congestion that scale non-linearly with architectural complexity (Luo et al., 2022; Kobbaey and Bilquise, 2023). Conflict-free coordination integrates pacing and routing with real-time state monitoring to enforce rules that prevent known failure modes: blocking door release when corridors exceed occupancy thresholds, delaying boarding initiation until deboarding subsides, and coordinating multi-aircraft operations to avoid simultaneous peak loads (Rott, Schultz and Fricke, 2023; Tang et al., 2025). These rules embed domain knowledge that human coordinators apply heuristically and inconsistently under time pressure (Schultz and Fricke, 2011), and automation delivers the consistency required for downstream synchronisation (Wu and Caves, 2004; Okwir, Amouzgar and Ng, 2025; Graves and Tomlin, 2003).

The turnaround itself is a tightly coupled serial process where sub-activities unfold under precedence constraints, making cycle time highly sensitive to variability at any critical-path stage (Wu and Caves, 2004) and mirroring manufacturing systems theory in which variability propagation in serial production lines amplifies cycle-time variance non-linearly (Buzacott and Shanthikumar, 1993; Dallery and Gershwin, 1992). Boarding occupies the critical position because effective service rate is constrained by a narrow aisle, limited bin space, and behavioural heterogeneity; even minor irregularities in the arrival stream propagate downstream and extend Gate Occupation Time. Realised boarding duration depends less on nominal sequence than on a small set of congestion-related parameters such as row pitch, seat density, aisle-clearing time, and simultaneous stowage

(Steffen, 2008; van den Briel et al., 2005). Physics-inspired and stochastic queueing models show that seat and aisle conflicts are multiplicative, with an early aisle block creating a shockwave impeding each subsequent passenger (Schultz, 2018; Ferrari and Nagel, 2005), and field-calibrated models confirm that outside-in or window-first methods deliver benefits only when arrivals are sufficiently dispersed; under high arrival variance, even optimal seat-assignment policies degrade rapidly (Steffen and Hotchkiss, 2012). The implication is that the true target of intervention is not the seating sequence but the variance of the arrival process into the aisle: Kingman's VUT equation makes this precise, with waiting time proportional to the product of variance, utilisation, and service time, and variance effects dominating at high utilisation (Hopp and Spearman, 2011). Event-log analyses confirm that flights within the same aircraft type and passenger-count band still display substantial dispersion in realised boarding windows, demonstrating that without upstream regulation, stochastic gate-level fluctuations propagate into milestone deviations (Schultz, Rosenow and Olive, 2022). The turnaround therefore behaves as a variability-sensitive serial system in which stabilising the input stream is the most powerful lever for controlling overall performance.

2.2.2 Evidence Traditions and the Real-Time Rule-Based Mechanism

Three research traditions converge on one conclusion: upstream flow regularity, not seat sequence, governs boarding performance. Boarding-policy studies show that outside-in and Steffen-style sequences dominate only when arrivals are dispersed and collapse under bursty inflow (Steffen, 2008; Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015). Process-mining of A-CDM event logs reveals dozens of operational variants persisting under mature governance: Rott, Schultz and Fricke (2023) identified 47 distinct process variants across 50,000+ events, and De Falco et al. (2023) found 35 to 45 per cent of turnarounds with at least one milestone violation, originating not in random noise but in predictable structural dependencies amenable to direct control (Schultz, Rosenow and Olive, 2022; van der Aalst, 2016). Predictive analytics achieve 70 to 85 per cent accuracy on milestone deviations through elastic-net, gradient-boosting and neural-network models (Fleurquin, Ramasco and Eguíluz, 2013; Okwir, Amouzgar and Ng, 2025; Tang et al., 2025), but forecasts identify when boarding will overrun without

preventing the physical-flow events that drive the overrun (Wu and Caves, 2004; Hopp and Spearman, 2011); errors concentrate in the distributional tail where forecasts would be most valuable, and decision-making research shows information overload routinely prevents action on accurate forecasts (Kahneman, 2011).

The rtBRMS evaluated here is an event-driven rule engine that (i) modulates entry rates by actuating door states in response to live tunnel and aisle congestion signals, (ii) orchestrates topology-aware routing across more than 60 access nodes (aircraft doors, jet-bridge controllers, tunnel-segment sensors, and corridor partition gates linked through the rtBRMS event bus) so domestic and international streams do not interfere, and (iii) enforces pre-validated congestion-avoidance rules (occupancy, service-rate and clearance thresholds) that keep work-in-process within control limits. Critically, the system removes the human-error risk of manual sequencing in shared-area tunnels, a recurrent issue at airports where incorrect sequencing has misrouted international passengers into domestic corridors and bypassed passport control. Because actuation is rule-governed and event-logged, the mechanism is transparent and auditable, operationalising Little, Kingman and Theory of Constraints prescriptions for the gate (Little, 1961; Kingman, 1961; Goldratt, 1984).

A-CDM defined six critical milestones (ALDT, AIBT, TOBT, TSAT, AOBT, TLDT) for stakeholder synchronisation (Eurocontrol, 2017), but the cited 15 to 30 per cent taxi-delay reductions (SESAR Joint Undertaking, 2016; Guo et al., 2020) derive from pre-post comparisons without quasi-experimental controls and aggregate across gate types that the literature itself shows to be heterogeneous (Shadish, Cook and Campbell, 2002; Rott, Schultz and Fricke, 2023). The empirical evaluation in this thesis corrects both the within-process gap (boarding/deboarding variance) and the aggregation bias through a 48-stratum field experiment at Mashhad International Airport (MHD), varying gate architecture, temporal bands, day type and flight type, with event-level logs aggregated to flight-level analytics analysed by Welch t-tests, Type-III General Linear Models and Firth-penalised logistic regression (Pellegrini, Castelli and Pesenti, 2017)

2.3 ORGANISATIONAL ASPECTS OF GATE OPERATIONS

Gate operations are coordinated across airline, airport, and ground-handling organisations with overlapping but distinct decision rights, and event-log reconstructions of turnarounds reveal persistent variability in routines under mature performance governance: the same flight category instantiates multiple process variants, implying that local teams exercise discretion under time pressure to resolve conflicts at doors, tunnels, and corridors, a plausible origin of dispersion when inflow to the aisle is not actively regulated (Rott, Schultz and Fricke, 2023; Schultz and Fricke, 2011). At the planning–operations boundary, gate-assignment and recovery research formalises the resource side of coordination, with scarce gates, blocking constraints between neighbouring stands, and shadow restrictions that prevent overlap (Dorndorf, Jaehn and Pesch, 2008, 2010, 2016); yet day-of-operations work shows that formal escalation paths are frequently bypassed under time pressure, with agents making ad hoc decisions about door sequencing and operations controllers negotiating informal priority agreements (Evler et al., 2022; Okwir, Amouzgar and Ng, 2025). This gap between planned escalation and actual decision-making creates a coordination fragility that rtBRMS addresses by embedding rule-based decision logic directly into the execution layer (Gehlen and Ronzani, 2025), absorbing the multi-stakeholder variability through transparent, auditable rules rather than opaque algorithmic decisions; the challenge is not to eliminate operator discretion (which captures tacit knowledge formal SOPs do not) but to provide guardrails that limit ad-hoc-induced variance while preserving flexibility for genuine exception handling.

Gate operations are also shaped by exogenous constraints. Passenger-segregation requirements are critical at airports handling both domestic and international traffic through shared gate infrastructure, where incorrect door sequencing has produced misrouting incidents requiring terminal evacuation and re-screening; rtBRMS enforces compliance-safe routing through real-time state validation, ensuring physical separation of streams until designated processing. Safety separations between adjacent stands constrain release timing, and shared-access configurations create bidirectional flow conflicts and ground-equipment contention (Moreira et al., 2023; Tang et al., 2025) that planning-level shadow restrictions cannot dynamically resolve (Dorndorf, Jaehn and Pesch, 2008); rtBRMS

provides the dynamic enforcement static scheduling cannot, monitoring corridor occupancy in real time to maintain separations without conservative buffers that inflate GOT. Regulatory frameworks (EASA, FAA) impose minimum turnaround times, mandatory safety briefings, accessibility, and identification-verification requirements as hard temporal constraints (ICAO, 2018; Eurocontrol, 2019), requiring execution-layer automation to be compliance-aware.

The organisation of gate work is therefore best understood as work design rather than scheduling alone. When 60 to 70% of turnaround variance originates in boarding/deboarding, the prescription is to redesign passenger release, door sequencing, and corridor routing to suppress variance at source rather than monitoring it after propagation (Rott, Schultz and Fricke, 2023; van der Aalst, 2016). The aisle is the scarce resource and interference grows non-linearly with crowding (Steffen and Hotchkiss, 2012; Jaehn and Neumann, 2015; Schultz, 2018): releasing 10 additional passengers per minute beyond aisle service capacity inflates boarding time by 30 to 50% through cascading interference, so passenger-release timing must be treated as a primary work-design parameter, with adaptive rules adjusting release rates to real-time corridor and aisle states. Architectural complexity then determines how difficult it is to maintain conflict-free routes, and queueing theory (Kingman, 1961) predicts that variance reduction yields disproportionately larger gains at complex gates, formalised in Study 1 as Hypothesis S1-H4: rtBRMS effects on GOT should be amplified at Types 3 and 4 (shared-access, multi-door) relative to Types 1 and 2 (single-access). The system's capacity to interconnect more than 60 doors converts architectural complexity from a vulnerability into a managed parameter, with airports advised to prioritise installation at their most complex configurations. By formalising routine task allocation and coordination through automated rule enforcement, rtBRMS reduces cognitive load and frees operators for higher-value disruption management (Schmidberger et al., 2009; Gehlen and Ronzani, 2025), provided operators perceive the automation as reliable, transparent, and supportive rather than autonomy-threatening (Lee and See, 2004; Parasuraman and Riley, 1997; Endsley, 2017; Sheridan and Parasuraman, 2005).

2.4 PASSENGER-FLOW DYNAMICS AND QUEUEING-THEORETIC FOUNDATIONS

Queueing theory provides the mathematical foundation for understanding how variability in arrival patterns and service times translates into waiting and cycle-time inflation in capacity-constrained systems (Kingman, 1961; Whitt, 1993; Gross et al., 2008): performance degrades non-linearly as utilisation approaches capacity because high utilisation leaves little slack to absorb stochastic fluctuations (Hopp and Spearman, 2011). Little's Law ($L = \lambda W$) establishes that reducing cycle time requires either lowering work-in-process or raising throughput (Little, 1961), and Kingman's formula extends this by showing that waiting time in a G/G/1 queue is approximately:

$$W \approx (\rho / (1 - \rho)) \times ((C_a^2 + C_s^2) / 2) \times (1 / \mu)$$

where ρ is utilisation, C_a^2 and C_s^2 are the squared coefficients of variation of inter-arrival and service times, and $1/\mu$ is mean service time. Three properties follow: waiting grows super-linearly with utilisation, variance in arrivals and service amplifies waiting proportionally to the sum of squared coefficients of variation, and reducing variance at source delivers disproportionately larger benefits at high utilisation. Applied to the gate, controlling passenger arrival variance (the dominant component of c^2_a) is therefore the primary lever for compressing boarding-window duration and Gate Occupation Time (Schultz, 2018; Steffen and Hotchkiss, 2012; Moreira et al., 2023; Rott, Schultz and Fricke, 2023). In serial queueing systems, variance also propagates and amplifies through the variability propagation law of factory physics (Hopp and Spearman, 2011): passenger flow exemplifies this, with variance at gate entry compounding through doors, corridors, and aisle, and discrete-event simulations showing 30 to 50% larger reductions in total boarding time when variance is suppressed at upstream entry rather than downstream (Schultz, 2018; Jaehn and Neumann, 2015; Goldratt, 1984).

Three layers generate gate-proximate variability. Passenger-level heterogeneity in walking speed (0.8 to 1.6 m/s), baggage volume, mobility, and behavioural compliance produces a stochastic arrival process whose service-time coefficient of variation has been measured at approximately 0.5 to 0.7 in narrow-body boarding studies (Schultz, 2018;

Steffen and Hotchkiss, 2012). Spatial-geometric constraints (single-aisle aircraft, aisle width near 0.5 m, row pitch 0.76 to 0.81 m) create a fixed serial bottleneck where the lever is not geometry but the rate and timing of release (Jaehn and Neumann, 2015). Coordination-level effects compound both: large uncontrolled batch releases (30 to 50 passengers) exceed aisle service capacity and trigger non-linear congestion, with bursty flights showing markedly longer boarding durations than paced flights under comparable conditions, with process-mining and trajectory studies identifying inflow variability as a leading driver of within-class dispersion (Rott, Schultz and Fricke, 2023; Schultz, Rosenow and Olive, 2022). Physics-inspired models treat boarding as a particle system in which total time is dominated by the longest blocking chain, increased by bursty inflow and shortened by paced inflow (Bachmat et al., 2006, 2009; Ferrari and Nagel, 2005; Hutter, Jaehn and Neumann, 2019). The operational signature of instability is therefore dispersion in boarding/deboarding windows, lower effective throughput, and extended GOT, which propagates through 60 to 70% of total turnaround variance into TOBT/TSAT unreliability and milestone violations cascading into departure delays (De Falco et al., 2023; Eurocontrol, 2017).

Two execution-layer implications follow. First, pacing precedes policy: without regulating the rate of entry, even well-designed sequencing rules lose effectiveness, while modest pacing restores the performance predicted by outside-in or window-first logics (van den Briel et al., 2005). Second, topology-aware routing reduces cross-flow interference, with shared-access corridors reducing effective capacity by 30 to 40% relative to dedicated configurations (Tang et al., 2025; Luo et al., 2022; Kobbaey and Bilquise, 2023). Theory of Constraints prescribes maintaining bottleneck flow without starvation or blocking and subordinating non-bottleneck processes to bottleneck rhythm (Goldratt and Cox, 2004), and discrete-event simulations confirm 20 to 35% reductions in boarding duration under bottleneck-protection policies (Jaehn and Neumann, 2015; Schultz, 2018). The convergent message is to suppress variance at the point of formation by capping WIP and synchronising inflow with aisle service, the function rtBRMS performs through real-time monitoring and dynamic release-rate adjustment (Gehlen and Ronzani, 2025).

2.5 BOARDING AND DEBOARDING EVIDENCE UNDER LIVE HETEROGENEITY

2.5.1 Boarding Methods and Sequence Strategies

The fundamental trade-off in boarding strategy design balances parallelism (multiple passengers loading simultaneously) against interference (collisions when passengers compete for limited aisle space) (Steffen and Hotchkiss, 2012; Schultz, 2018). Random boarding maximises parallelism but induces high interference, producing moderate but high-variance times (Bachmat et al., 2006). Back-to-front (rear-seated first) reduces interference but limits parallelism and often performs worse than random because it creates synchronised conflicts within each zone (van Landeghem and Beuselinck, 2002; Steffen, 2008). Outside-in (window-middle-aisle) and Steffen's optimal method (alternating rows and seats) achieve superior performance, with outside-in reducing time by 10 to 20% relative to back-to-front and Steffen's method achieving 30 to 40% reductions relative to random (Steffen and Hotchkiss, 2012; Jaehn and Neumann, 2015). However, these methods impose operational complexity (seat-specific sequencing, passenger compliance, coordination overhead) limiting practical adoption in short-haul operations (Schultz, 2018; Moreira et al., 2023).

The boarding-sequence literature has, however, generated more theoretical optimism than field-validated benefit. Steffen's (2008) optimal method has never been adopted at scale because it requires seat-by-seat sequencing that defeats real passengers' tolerance for boarding logistics, and the 30 to 40% reductions reported in the literature are an artefact of compliant simulated agents that do not exist in live operations (Steffen and Hotchkiss, 2012; Moreira et al., 2023). The deeper problem is that the canonical literature treats seat-sequence as the design variable when the field-traceable evidence repeatedly identifies arrival-pattern variance as the dominant driver: under bursty inflow even the theoretically optimal sequence collapses, while under paced inflow even nominally inferior sequences perform near-optimally (Schultz, 2018; Jaehn and Neumann, 2015). The methodological consequence is that two decades of seat-sequence research have optimised the wrong lever, and the policy consequence is that airports have invested in boarding-method changes that produce negligible field gains while leaving the actual variance

source, gate-entry timing, untouched. rtBRMS reverses this priority: control entry timing, accept whatever seat order results, and let the variance suppression do the work that sequencing cannot (Gehlen and Ronzani, 2025; Tang et al., 2025).

2.5.2 Deboarding Dynamics and Interference Mechanisms

Deboarding exhibits distinct dynamics due to differences in motivation, spatial constraints, and coordination. Deboarding passengers are typically more motivated to exit quickly (connection urgency, baggage retrieval, desire to leave), producing higher walking speeds and more aggressive spatial competition (Schultz, 2018; Moreira et al., 2023). Deboarding shares the same spatial bottlenecks as boarding (narrow aisles, limited door capacity, shared corridors) (Steffen and Hotchkiss, 2012; Tang et al., 2025).

The deboarding evidence base is thinner than the boarding literature, and the descriptive claim that deboarding has lower mean but higher variance rests almost entirely on a single source (Schultz, 2018) supplemented by simulation work (Moreira et al., 2023); independent field replication is largely absent. This monoculture is consequential because deboarding variance is the parameter that governs whether shared-corridor boarding can be initiated safely, and the literature has not established whether the reported variance pattern generalises across aircraft types, terminal geometries, and passenger compositions or merely reflects the test conditions of the original study. A second weakness is that the deboarding-boarding coordination problem is consistently identified as critical (Tang et al., 2025; Rott, Schultz and Fricke, 2023) yet no published study has measured the operational cost of deboarding-induced uncertainty on subsequent boarding in live conditions; the field has converged on a coordination problem it has not actually quantified. The 48-stratum design of this thesis provides exactly that quantification.

2.5.3 Synthesis Model of Interference Mechanisms

Integrating boarding-method, deboarding, and spatial-constraint evidence yields a synthesis model of four interference types: aisle interference (passengers blocking each other during seat access); door interference (queue formation when arrival rate exceeds door capacity); corridor interference (cross-flow conflicts when boarding/deboarding

compete for shared corridors); and spatial saturation (queue spillback blocking upstream processes when downstream capacity is exhausted) (Schultz, 2018; Moreira et al., 2023; Tang et al., 2025).

Aisle interference arises from cabin geometry: passengers traverse narrow aisles sequentially, and seat-access activities block followers (Steffen and Hotchkiss, 2012). Magnitude depends on density, baggage, and seat-access duration, with interference rising non-linearly as density approaches capacity (Schultz, 2018). Door interference occurs when arrival rate at boarding doors exceeds processing capacity, inducing queues in waiting areas that delay initiation and inflate GOT (Moreira et al., 2023). Corridor interference emerges in shared-access configurations where simultaneous operations create bidirectional conflicts reducing effective corridor capacity (Tang et al., 2025; Luo et al., 2022). Spatial saturation is the cascading failure where congestion at one bottleneck propagates upstream, blocking earlier stages and creating system-wide gridlock (Rott, Schultz and Fricke, 2023; Gehlen and Ronzani, 2025).

These mechanisms interact through feedback loops that amplify variability. Door interference increases corridor density, exacerbating corridor interference and accelerating saturation; saturation delays deboarding completion, forcing delayed boarding initiation and inflating door interference for subsequent operations (Schultz, 2018; Tang et al., 2025). Self-reinforcing congestion spirals can persist through the turnaround. Breaking these requires controlling arrival patterns at source to prevent door and corridor interference before saturation can emerge (Gehlen and Ronzani, 2025; Moreira et al., 2023).

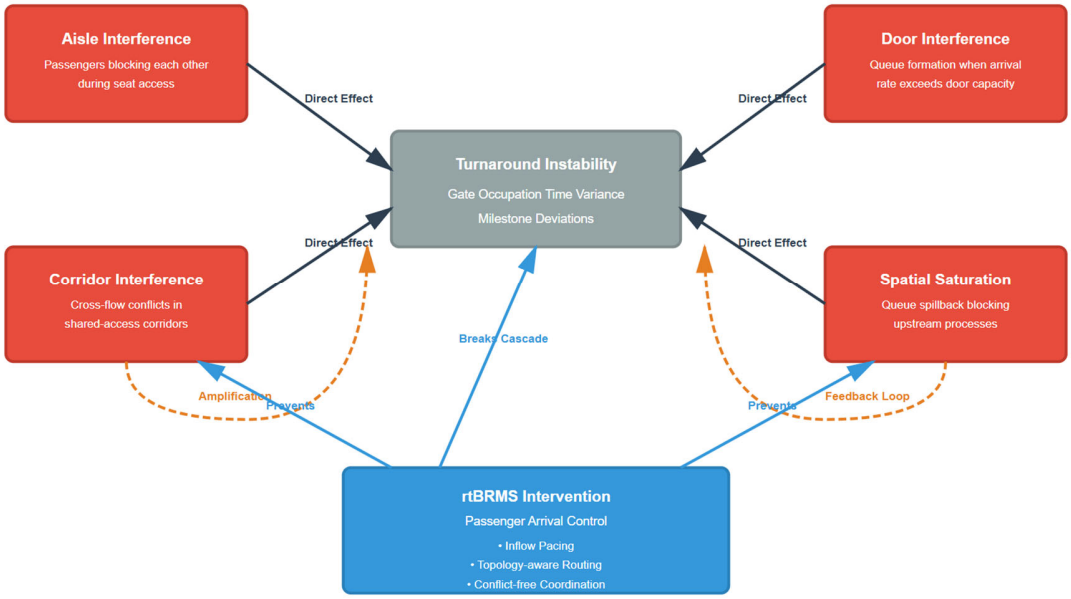


Figure 2-3 Synthesis Model of Boarding and Deboarding Interference Mechanism (Own illustration based on synthesis of boarding research (Schultz, 2018; Steffen & Hotchkiss, 2012) and multi-gate coordination studies (Moreira et al., 2023; Tang et al., 2025)).

Figure 2.3 presents the synthesis model of interference mechanisms, illustrating the causal relationships and feedback loops among aisle interference, door interference, corridor interference, and spatial saturation. Solid arrows indicate direct causal effects; dashed arrows indicate feedback loops that amplify variability. The model highlights that rtBRMS interventions targeting passenger arrival control (shown in blue) can interrupt the cascade by preventing door and corridor interference, thereby breaking the feedback loops that drive spatial saturation and turnaround instability.

2.6 WORK ORGANISATION AND PROCESS CONTROL AT CHOKEPOINTS

Ground handling at gates involves multiple roles with distinct authority: gate agents manage passenger processing, ramp coordinators oversee servicing and equipment, and operations controllers monitor turnaround progress across gates within defined boundaries (Ashford, Mumayiz and Wright, 2013; Evler et al., 2022; Schultz and Fricke, 2011; Okwir, Amouzgar and Ng, 2025). The introduction of rtBRMS raises questions of human-automation authority allocation: automation executes routine decisions faster and more consistently but lacks the contextual adaptability operators apply to exceptions (Lee and

See, 2004; Endsley, 2017), so routine release decisions should be allocated to automation while operators retain authority for exceptions, with explainable, adjustable, and supervisory-override design principles (Parasuraman and Riley, 1997; Sheridan and Parasuraman, 2005; Gehlen and Ronzani, 2025; Tang et al., 2025).

Door opening, passenger release, and corridor routing have grown as station-specific routines, and event-log studies confirm that even within a single airport, multiple execution variants coexist and correlate with milestone dispersion when inflow is not actively governed (Rott, Schultz and Fricke, 2023). Flight-gate scheduling research formalises why these routines are fragile under day-of-operations uncertainty, with shadow restrictions and stochastic perturbations forcing real-time reallocations at the stand (Dorndorf, Jaehn and Pesch, 2008, 2010, 2016). Two decades of boarding research show the limits of procedural control under peak load: aisle-interference-minimising strategies reduce boarding only when upstream flow is cooperative (van den Briel et al., 2005; Jaehn and Neumann, 2015), and without rules that pace entry, sequencing devolves into reactive queue handling that cannot prevent long blocking chains (Bachmat et al., 2009; Ferrari and Nagel, 2005).

Gate work is also a high-tempo cognitive environment where situation-awareness theory shows operators must perceive, comprehend, and project flows, occupancy, door status, and cabin progress; opaque automation drives miscalibrated reliance (Endsley, 1995, 2015; Lee and See, 2004). The Job Demands–Resources model predicts that stable arrival flow and explicit route authorisations raise resources and improve engagement and performance (Bakker and Demerouti, 2007); rule-based automation can encode tacit operator knowledge into executable procedures provided rules reflect operational requirements and operators perceive automation as supportive (Schultz and Fricke, 2011).

Four preconditions enable safe rule-based control: auditability through event logging; predictable behaviour under surge through credible pacing and topology-aware separation; human-centred transparency that communicates the reason for each rule (predicted conflict at merge M in T seconds; aisle WIP exceeds cap); and safe fallback to

manual SOPs when sensing degrades. Performance measurement must also evolve from aggregate, lagging, siloed indicators (Rott, Schultz and Fricke, 2023; Wu and Caves, 2000) toward closed-loop frameworks in which durations, queue lengths, and occupancy are captured continuously and parameters adjusted, implementing learning that improves over time (Hopp and Spearman, 2011; DeLone and McLean, 2003).

2.7 HUMAN FACTORS IN DIGITAL GATE OPERATIONS

Four established frameworks are routinely invoked to explain how operators respond to workplace automation: human-automation interaction (Lee and See, 2004), Job Demands-Resources (Bakker and Demerouti, 2007), TAM2 (Venkatesh and Davis, 2000), and the IS Success Model (DeLone and McLean, 2003). Each was developed in a domain remote from real-time airport gate work, laboratory automation tasks, knowledge-work organisations, enterprise software, and information systems respectively, and each has been transposed into aviation contexts more often than it has been independently validated there.

Three substantive limitations follow. First, none of the four frameworks was constructed for operators whose decisions have ten-second latency consequences for downstream schedule integrity, and the constructs they specify (calibrated reliance, engagement, perceived usefulness, satisfaction) were operationalised under leisurely deliberation conditions that do not match gate-floor cognitive demands. Second, the frameworks have rarely been tested jointly: the human-automation literature treats reliance as an end-state, JD-R treats engagement as an end-state, TAM2 treats use intention as an end-state, and IS Success treats satisfaction as an end-state, with the result that each framework claims terminal status for its own focal construct and the field lacks a tested integration. Third, the assumption that these frameworks transfer cleanly to execution-layer automation is unsupported: TAM2 and IS Success were built for systems that operators choose to use, whereas rtBRMS is a system operators must use, and the voluntariness assumption embedded in the acceptance literature does not survive the transposition. The Study 2 model in Section 2.11.2 therefore does not adopt these four frameworks

uncritically but uses them as construct sources whose joint structural specification is itself an empirical claim to be tested rather than a settled theoretical position.

Human-Automation Interaction (Lee and See, 2004; Parasuraman and Riley, 1997; Endsley, 2017) treats predictability as the cognitive substrate of human reliance on automation. Reliance is shaped by performance, process, and purpose: over-trust produces complacency, under-trust produces disuse, and calibrated reliance requires that system behaviour be consistent and transparent enough for operators to construct accurate forward models of system response. Situation-awareness theory (Endsley, 1995, 2017; Wickens, 2008) extends this by partitioning operator cognition into perception, comprehension, and projection, with automation able either to enhance or to degrade each level depending on transparency and cognitive-load management (Sweller, 1988).

The Job Demands–Resources model (Bakker and Demerouti, 2007, 2017; Demerouti et al., 2001) specifies a motivational pathway in which job resources (autonomy, predictability, support) and reduced demands (lower strain, fewer interruptions) generate work engagement, which in turn drives task performance. Meta-analytic evidence shows engagement to be a robust intervening process between resources and performance (Christian, Garza and Slaughter, 2011), and the dual nature of the JD-R process, resource-driven motivation; demand-driven strain reduction, maps directly onto the AUT, JSR, and ENG constructs of the Study 2 model.

The Technology Acceptance Model 2 (Venkatesh and Davis, 2000; Davis, 1989; Venkatesh et al., 2003) specifies the cognitive-instrumental processes (result demonstrability, output quality, job relevance) through which system characteristics translate into perceived usefulness. In Study 2, perceived usefulness is operationalised as Perceived Performance Contribution (PPC), and the TAM2 instrumental processes serve as the theoretical mechanism linking Perceived System Predictability (PSP) to PPC.

The DeLone and McLean Information Systems Success Model (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008) positions System Satisfaction (SS) as

the highest-order attitudinal outcome that integrates system quality, information quality, and net benefits into a single global evaluation. In Study 2, SS is the terminal outcome of the structural model, drawing on cognitive (PSP), motivational (ENG), behavioural (IWP), and throughput (EMP) channels.

For rtBRMS, the joint implication of these four frameworks is that operators internalise stabilised flow as predictability (Human-Automation Interaction), convert predictability into engagement and contribution beliefs (JD-R, TAM2), and synthesise the resulting performance and productivity gains into a global satisfaction judgement (IS Success). The structural model in Section 2.11.2 specifies the directional paths through which this transmission operates, and the hypotheses in Section 2.11.3 formalise each path as a testable prediction.

2.8 IDENTIFIED GAPS IN CURRENT RESEARCH

2.8.1 Overview of Gap Analysis Methodology

The literature review examined the relevant domains influencing rtBRMS and critically assessed them. Even at the level of underlying terminology, no uniform definition exists for "execution control", "flow management", or "real-time intervention" (Rott, Schultz and Fricke, 2023; Gehlen and Ronzani, 2025; Tang et al., 2025); explicit definitions for this thesis are presented in Section 2.2.

Although important factors and findings exist within individual domains, the holistic approach required to understand rtBRMS implementation and effectiveness is not fulfilled. The gaps are summarised below and graphically illustrated. Each domain is examined to identify what is addressed and what remains unexplored. The conceptual framework distinguishes blue (adequately addressed), red (insufficiently addressed), and dashed arrows (partial coverage where general effects are noted but interactions remain underspecified). The rtBRMS research domain emerges at the intersection of three theoretical foundations (Figure 2.5).

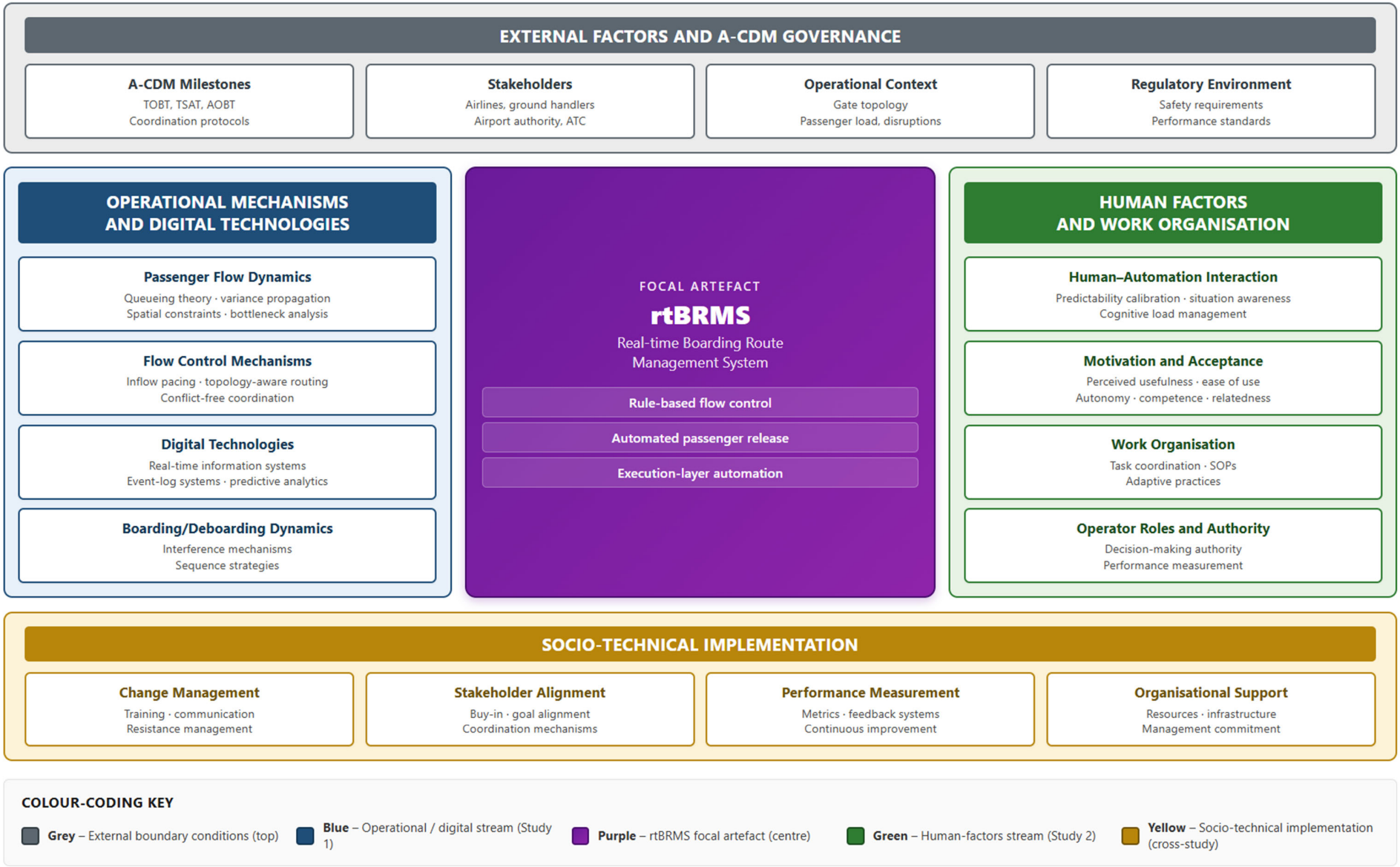


Figure 2-4 Conceptual Framework of the Influencing Determinants of rtBRMS - Five interacting determinant streams converging on the real-time boarding route management system at the airport gate

Figure 2.4 is the master conceptual map of the thesis and is read in five layers, each carrying a distinct theoretical commitment.

The top grey band, External Factors and A-CDM Governance, marks boundary conditions the gate cannot control but must respond to: A-CDM milestones (TOBT, TSAT, AOBT) and coordination protocols; the multi-stakeholder ecology (airlines, ground handlers, airport authority, ATC); operational context (gate topology, passenger load, day-of-operations disruptions); and the regulatory envelope (safety requirements, performance standards). These appear in Study 1 as stratification dimensions and as the fixed regulatory backdrop, not as manipulable variables.

The central purple panel is the focal artefact, the rtBRMS itself, decomposed into rule-based flow control, automated passenger release, and execution-layer automation. Purple is reserved for this artefact across the chapter. Its central position signals that the framework is causally bidirectional: every surrounding stream both shapes and is shaped by what the rtBRMS does at the gate.

The left blue panel (Operational Mechanisms and Digital Technologies) is the domain of Study 1: passenger-flow dynamics (queueing theory, variance propagation, bottleneck analysis); flow-control mechanisms (inflow pacing, topology-aware routing, conflict-free coordination); digital technologies (real-time information systems, event-log capture, predictive analytics); and boarding/deboarding dynamics (interference mechanisms, sequence strategies). Each stream supplies inputs to the artefact and receives feedback from it.

The right green panel (Human Factors and Work Organization) is the domain of Study 2 and structurally mirrors the operational panel: human-automation interaction (predictability calibration, situation awareness, cognitive-load management); motivation and acceptance (perceived usefulness, ease of use, autonomy, competence, relatedness); work organization (task coordination, SOPs, adaptive practices); and operator roles and authority (decision-making authority, performance measurement). The blue-green

symmetry embodies the dual-study architecture: rtBRMS effectiveness is jointly determined by what the system does to flow and how operators respond to it, with neither side reducible to the other.

The bottom yellow band (Socio-Technical Implementation) is the cross-study context: change management (training, communication, resistance management); stakeholder alignment (buy-in, goal alignment, coordination mechanisms); performance measurement (metrics, feedback systems, continuous improvement); and organizational support (resources, infrastructure, management commitment). Placing this band at the bottom inverts the conventional implementation hierarchy: implementation conditions support the technical and human mechanisms rather than dictating them, operating as a moderating envelope. Empirically, this band is operationalized through the stratification dimensions of Study 1 and the eight contextual moderators of Study 2.

The color-coding key is the navigational device that anchors every subsequent figure in Chapter 2: grey = external boundary, blue = operational/digital (Study 1), purple = rtBRMS artefact, green = human factors (Study 2), yellow = cross-study implementation. The same five colors reappear in Figures 2.5 to 2.9, allowing any topic to be traced back to its parent layer by color alone.

Read together, the five layers articulate the thesis's central theoretical claim: that rtBRMS effectiveness is the joint product of an operational mechanism (blue), an operator user-experience mechanism (green), an external boundary (grey), and an implementation envelope (yellow), all converging on a single execution-layer artefact (purple), and that no single layer is sufficient on its own to explain the empirical record.

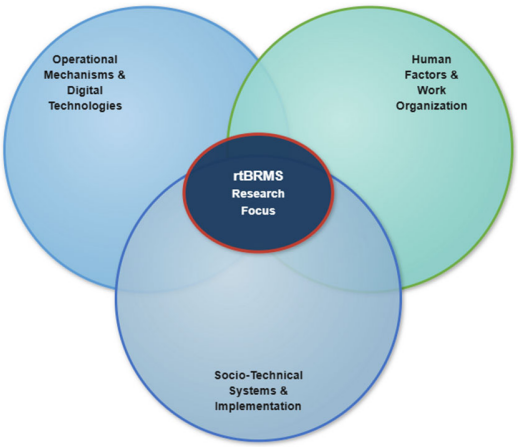


Figure 2-5 rtBRMS research focus at the intersection of key - Own illustration based on synthesis of operational mechanisms (Hopp & Spearman, 2011; Schultz, Rosenow and Olive, 2022), human factors (Lee & See, 2004; Endsley, 2017), and socio-technical systems (Clegg, 2000; Mumford, 2006; Trist & Bamforth, 1951).

Figure 2.5 illustrates the intersection of the three primary domains that determine rtBRMS effectiveness. The operational mechanisms domain encompasses passenger flow dynamics, queueing theory, spatial constraints, and flow control algorithms. The human factors domain includes operator predictability, situation awareness, cognitive load, motivation, and acceptance. The socio-technical implementation domain covers organizational coordination, change management, performance measurement, and stakeholder alignment. The central intersection, where all three domains overlap, represents the critical research gap that this thesis addresses: understanding how technical flow control capabilities, human operator responses, and organizational implementation conditions jointly determine whether rtBRMS can achieve operational effectiveness and sustained adoption in practice.

2.8.2 Domain of Impact: Operational Mechanisms & Digital Technologies

Digital technologies have increased sensor data, real-time analytics, and automated decision capabilities (Lee and Yu, 2018; Guo et al., 2020). Human-automation interactions divide into monitoring, cooperation, collaboration, and delegation (Parasuraman and Riley, 1997; Sheridan and Parasuraman, 2005). New technologies change how gate operations are executed, coordinated, and optimised (Rott, Schultz and Fricke, 2023; Gehlen and Ronzani, 2025; Tang et al., 2025).

What exactly influences short-haul operations when implementing real-time flow control, considering work organisation and operator demands, has not been clarified. Current research shows that arrival variance drives instability (Schultz, 2018; Steffen and Hotchkiss, 2012), that queueing theory predicts variance-reduction benefits (Kingman, 1961; Hopp and Spearman, 2011), and that simulations show 20 to 35% boarding-time reductions through controlled release (Jaehn and Neumann, 2015; Moreira et al., 2023). These remain largely theoretical or simulation-based; empirical validation under authentic flows, topologies, and coordination constraints is severely limited (Rott, Schultz and Fricke, 2023; Tang et al., 2025). Interactions across organisational boundaries are addressed in A-CDM literature but not sufficiently in terms of how real-time execution affects coordination dynamics, information sharing, and milestone governance (Eurocontrol, 2017; Okwir, Amouzgar and Ng, 2025). Bidirectional feedback loops between technical capabilities and human responses cannot be fully explained from current literature.

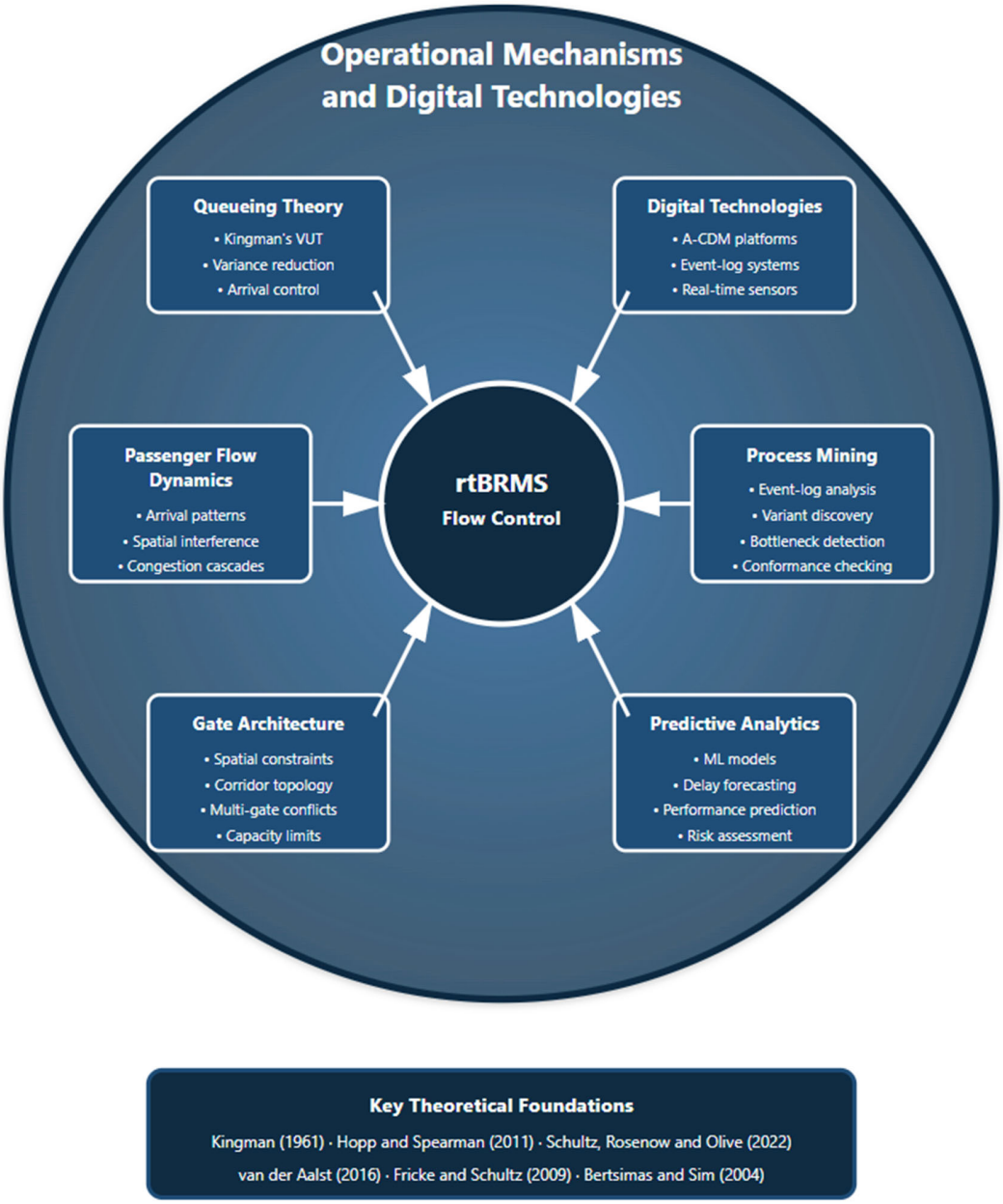


Figure 2-6 Domain of impact: operational mechanisms and digital technologies. Six theoretical components surround the rtBRMS flow-control hub at the center of the operational/digital domain. Own illustration based on synthesis of queueing theory (Kingman, 1961; Hopp and Spearman, 2011), process mining (van der Aalst, 2016), and airport operations research (Schultz, Rosenow and Olive, 2022; Fricke and Schultz, 2009).

Color rationale. The figure is rendered in blue because blue is the chapter-wide color for the operational and digital-technology domain (Figures 2.1, 2.2 and 2.4). The light-blue domain disc indicates that all six components belong to this domain; the dark-navy central hub denotes the rtBRMS flow-control artefact at the operational core; arrows from each component point inward to the hub to show that each theoretical input feeds the operational mechanism under study. The blue palette is reserved for content tested in Study 1.

Figure 2.6 depicts the coverage and gaps in the Operational Mechanisms & Digital Technologies domain. Blue areas indicate well-researched topics: passenger flow dynamics, queueing theory foundations, boarding method optimization, and A-CDM milestone frameworks. Red areas indicate research gaps: empirical validation of flow control in live operations, integration of real-time execution with A-CDM governance, operator response to automated release decisions, and organizational adaptation to execution-layer automation. Dashed arrows indicate partially understood interactions where theoretical predictions exist but empirical validation is lacking.

2.8.3 Domain of Impact: Human Factors & Work Organization

Human-factors research has elaborated the dimensions of predictability, situation awareness, cognitive load, and motivation that govern automation effectiveness (Lee and See, 2004; Endsley, 2017; Parasuraman and Riley, 1997), but how these dimensions specifically manifest in real-time gate flow control, where automation makes rapid release decisions that directly shape turnaround outcomes, has not been empirically investigated (Gehlen and Ronzani, 2025; Okwir, Amouzgar and Ng, 2025). Awareness requirements span gate, corridor, and system levels, yet existing research does not specify how rtBRMS should present information without inducing overload or mode confusion (Endsley, 2017; Wickens, 2008), and the cognitive-load tradeoff between fewer routine decisions and increased monitoring vigilance remains unexplored in airport contexts (Parasuraman and Riley, 1997). Motivation and acceptance are well studied in general (Davis, 1989; Venkatesh and Davis, 2000; Venkatesh et al., 2003) but have not been applied to execution-layer automation that constrains traditional coordination. From a work-organisation perspective, operators routinely improvise workarounds and apply tacit knowledge (Evler et al., 2022; Schultz and Fricke, 2011), yet how rtBRMS should integrate with these adaptive practices, formalising some decisions while preserving flexibility for genuine exceptions, remains an open question (Tang et al., 2025). Performance-measurement systems with the temporal resolution required for real-time feedback are likewise underdeveloped (Rott, Schultz and Fricke, 2023). The general principles of human-automation interaction are well established; their specific application to real-time gate flow control is not.

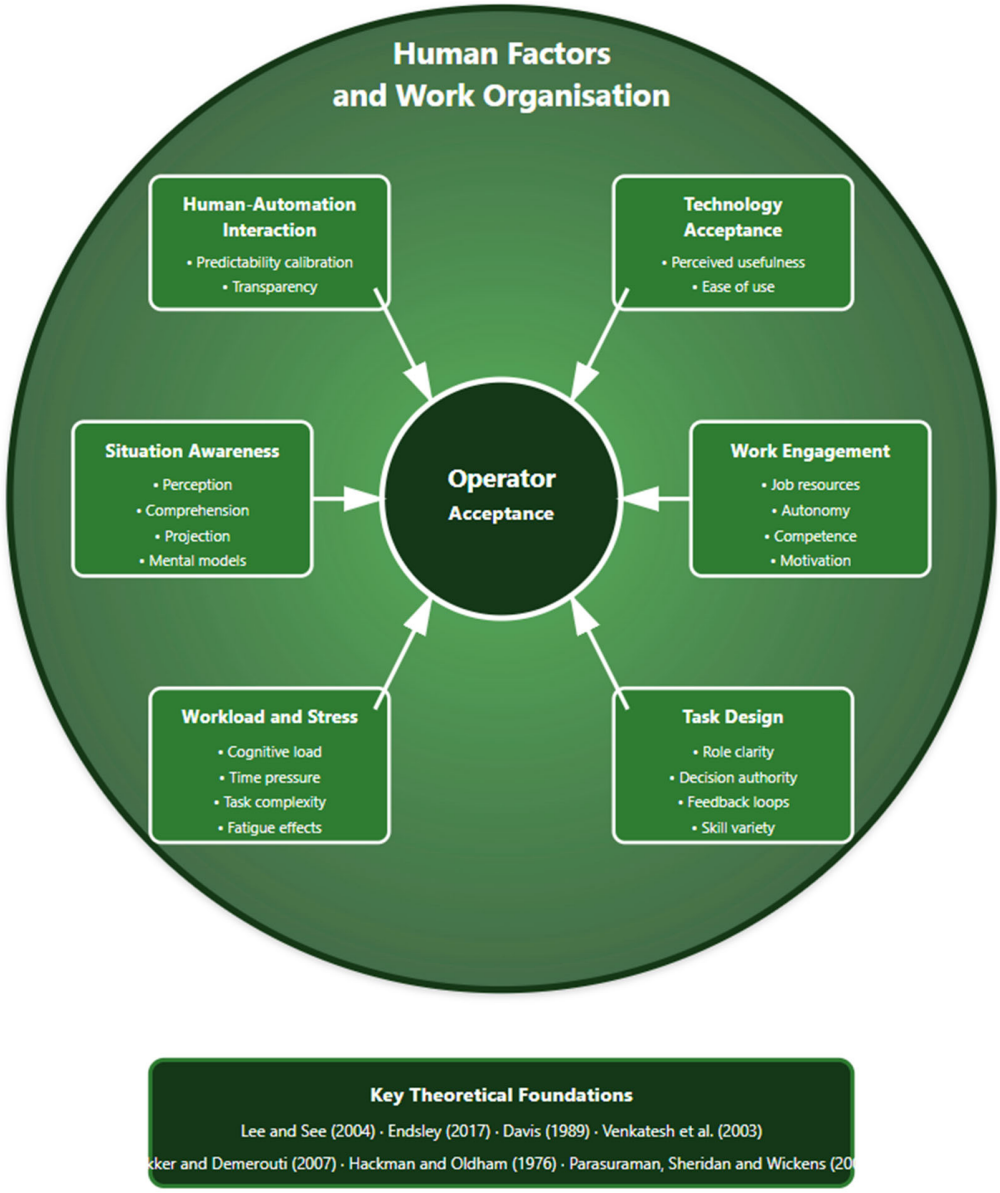


Figure 2-7 Domain of impact: human factors and work organization. Six theoretical components surround the operator-acceptance hub at the center of the human-factors domain. Own illustration based on synthesis of human–automation interaction theory (Lee and See, 2004; Parasuraman, Sheridan and Wickens, 2000), technology acceptance models (Davis, 1989; Venkatesh et al., 2003), situation awareness (Endsley, 2017), and work-engagement theory (Bakker and Demerouti, 2007; Hackman and Oldham, 1976).

Color rationale. The figure is rendered in green because green is the chapter-wide color for the human-factors and work-organization domain (Figures 2.1, 2.2 and 2.4). The light-green domain disc indicates that all six components belong to this domain; the dark-green central hub denotes operator acceptance as the focal outcome through which automation reaches the gate; arrows from each component point inward to the hub to show that each theoretical input feeds the operator-acceptance mechanism. The green palette is reserved for content surveyed in Study 2.

Figure 2.7 shows that while foundational human factors concepts (predictability, situation awareness, cognitive load, motivation) are well-researched in general aviation contexts (blue areas), their specific manifestation in rtBRMS implementation remains unexplored (red areas). Critical gaps include: operator predictability calibration for automated release decisions, situation awareness requirements for multi-gate coordination, cognitive load implications of monitoring versus manual control, motivation factors that drive acceptance or resistance, and integration of automation with adaptive work practices. Interactions between human factors and operational outcomes (dashed arrows) are theoretically predicted but empirically unvalidated.

2.8.4 Domain of Impact: Socio-Technical Systems & Implementation

Effective technology implementation requires coordinated adaptation of technical systems, work organisation, and human capabilities (Trist and Bamforth, 1951; Pasmore et al., 2019), but existing socio-technical research is limited when applied to real-time execution at the gate. Traditional approaches focus on stable production environments with clear organisational boundaries (Winby and Mohrman, 2018), whereas airport operations involve multiple organisations, dynamic conditions, and safety-critical coordination (Schultz and Fricke, 2011; Evler et al., 2022). The literature emphasises joint optimisation but offers limited guidance on sequencing implementation, managing transitions, or handling resistance when automation disrupts established practices (Okwir, Amouzgar and Ng, 2025), and the temporal dynamics of socio-technical adaptation, namely how predictability develops, how practices evolve, and how performance improves over time, are insufficiently theorised (Gehlen and Ronzani, 2025; Tang et al., 2025). Change-management frameworks (Kotter, 1996; Lewin, 1947) do not address the specific challenges of high-frequency execution-layer automation affecting multiple stakeholders, and although the IS Success Model (DeLone and McLean, 2003) offers useful constructs (system, information, and service quality, satisfaction, use, net benefits), it was developed for enterprise IS rather than real-time operational control, requiring empirical validation in this context. Stakeholder-alignment mechanisms across airlines, handlers, airports, and operators when systems redistribute authority remain inadequately addressed, as do

performance frameworks that demonstrate value to stakeholders with different objectives (airlines: OTP; handlers: efficiency; airports: capacity) (Rott, Schultz and Fricke, 2023).

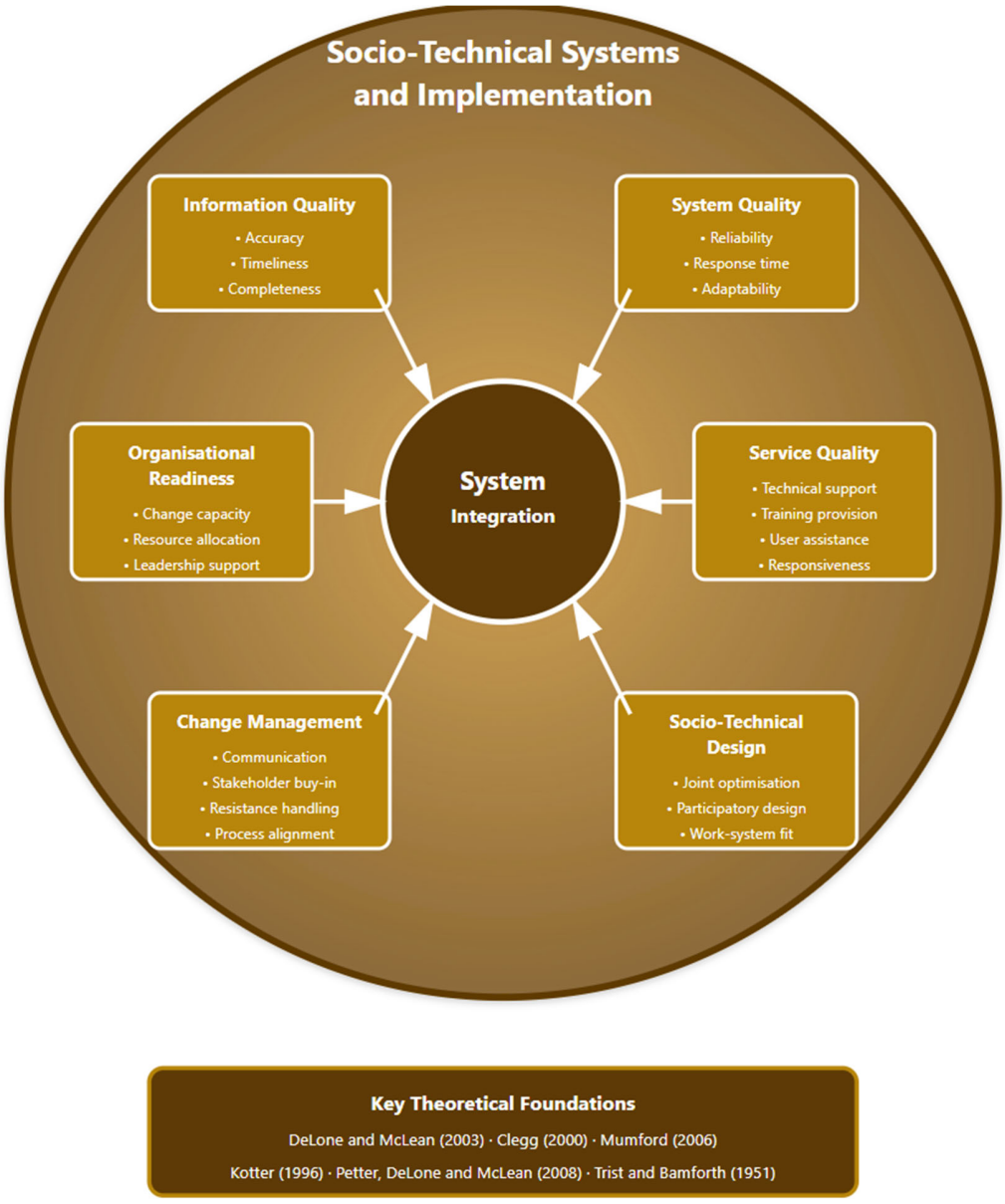


Figure 2-8 Domain of impact: socio-technical systems and implementation. Six theoretical components surround the system-integration hub at the center of the socio-technical implementation domain. Own illustration based on synthesis of the IS Success Model (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008), socio-technical systems theory (Clegg, 2000; Mumford, 2006; Trist and Bamforth, 1951) and change management (Kotter, 1996).

Colour rationale. The figure is rendered in amber because amber is the chapter-wide colour for the socio-technical and implementation domain (Figures 2.1, 2.2 and 2.4). The light-amber domain disc indicates that all six components belong to this domain; the dark-amber central hub denotes system integration as the focal outcome that knits

technology and people into a working socio-technical system; arrows from each component point inward to the hub to show that each theoretical input feeds the integration mechanism. The amber palette is reserved for content addressed across Study 1 and Study 2 as the implementation context.

Figure 2.8 illustrates that while general socio-technical principles are well-established (blue areas), their application to rtBRMS implementation in multi-stakeholder airport environments remains largely unexplored (red areas). Critical gaps include: implementation sequencing and transition management, stakeholder alignment across organizational boundaries, change management for execution-layer automation, performance measurement frameworks that demonstrate value to diverse stakeholders, and temporal dynamics of predictability development and work practice evolution. The interactions between implementation conditions and operational effectiveness (dashed arrows) are theoretically important but empirically unvalidated.

2.8.5 Integration Across Domains: The Central Research Gap

None of the research streams examined, operational mechanisms, human factors, or socio-technical implementation, adequately addresses the intersection of all three domains that determines rtBRMS effectiveness in practice. Operational research demonstrates technical feasibility through simulations but does not validate effectiveness under authentic human-organizational conditions (Schultz, 2018; Jaehn and Neumann, 2015). Human factors research establishes general principles of automation acceptance but does not apply them to real-time gate flow control contexts (Lee and See, 2004; Endsley, 2017). Socio-technical research provides frameworks for technology implementation but does not address the specific challenges of execution-layer automation in multi-stakeholder operational environments (Pasmore et al., 2019; Winby and Mohrman, 2018).

The central research gap, therefore, lies at the intersection of these three domains: understanding how technical flow-control capabilities, human-operator responses, and organisational implementation conditions jointly determine whether rtBRMS can achieve sustained operational effectiveness and stakeholder acceptance. This gap encompasses five specific questions that the current literature does not adequately address:

1- **Gap Question 1 - Operational Effectiveness. Can real-time passenger-release control reduce Gate Occupation Time variance and improve milestone stability in live operational environments with authentic passenger flows, gate topologies, and coordination constraints?**

2- **Gap Question 2 - Human Factors. How do operators perceive, calibrate predictability for, and respond to automated flow-control decisions? What factors determine appropriate predictability calibration, effective situation awareness, manageable cognitive load, and sustained motivation?**

3- **Gap Question 3 - Socio-Technical Integration. What implementation conditions (stakeholder alignment, change-management practices, performance-measurement frameworks, organisational support) enable successful rtBRMS adoption and sustained effectiveness?**

4- **Gap Question 4 - Temporal Dynamics. How do operational effectiveness, operator predictability, and organisational support evolve over time as experience accumulates, work practices adapt, and system refinements occur?**

5- **Gap Question 5 - Contextual Moderators. How do operational context factors (passenger load, gate topology, disruption frequency, organisational culture) moderate rtBRMS effectiveness and acceptance?**

These questions cannot be answered through simulation studies, laboratory experiments, or theoretical analysis alone. They require field research that implements rtBRMS in authentic operational environments and measures both operational outcomes and human-organisational responses (Rott, Schultz and Fricke, 2023; Gehlen and Ronzani, 2025; Tang et al., 2025). This thesis addresses Gap Questions 1, 2, and 3 directly through a quasi-experimental field study and a cross-sectional operator survey, and provides partial coverage of Gap Question 5 through stratified design and moderation analysis. Gap

Question 4 (longitudinal evolution) is identified as out of scope and reserved for future research.

Gap Questions 1–2 are mapped to the two core empirical studies.

Gap Question 1 corresponds to the operational-effectiveness dimension of RO1 and is operationalised through Study 1's quasi-experimental field design, in which 171 flights at Mashhad International Airport are observed across a fully crossed 48-stratum matrix defined by four gate topologies (Type 1: single-access 2–3 doors; Type 2: single-access ≥4 doors; Type 3: shared-area single-access; Type 4: shared-area multi-access ≥4 doors), three temporal periods (morning peak, midday, evening/night), two day types (weekday, weekend), and two flight types (domestic, international). The stratification ensures that the causal estimate of rtBRMS effectiveness is not confounded by the contextual factors (spatial layout, time-of-day demand patterns, day type, flight type) that the literature identifies as primary sources of turnaround variability (Schultz, 2018; Rott, Schultz and Fricke, 2023). Within each stratum, treatment and control flights are compared on Gate Occupation Time (GOT) in minutes, boarding-window duration, deboarding-window duration, and passenger throughput rate (passengers per minute), with covariate adjustment used to control for residual confounding from passenger count, shared access points, and self-check-in availability (Shadish, Cook and Campbell, 2002).

Gap Question 2 corresponds to the human-factors dimension of RO2 and is operationalised through Study 2's cross-sectional survey of 224 frontline operators (gate agents, ramp coordinators, boarding supervisors, security personnel, and ground-handling staff) who have direct experience with rtBRMS-managed flights, analysed via partial least squares structural equation modelling (PLS-SEM) to estimate the latent pathways linking perceived flow stability through perceived system predictability, perceived performance contribution, and work engagement to self-reported individual work performance, employee productivity, and system satisfaction (Hair, Hult, Ringle and Sarstedt, 2022). The measurement model employs validated multi-item scales for each construct, including the Utrecht Work Engagement Scale ultra-short form UWES-3 (Schaufeli et al., 2017), the Technology Acceptance Model 2 instruments (Venkatesh and Davis, 2000), and the

Individual Work Performance Questionnaire (Koopmans et al., 2013), ensuring that the latent variables capturing operator user-experience mechanisms are measured with established psychometric rigour rather than ad hoc single-item proxies.

Gap Question 3 is mapped to the socio-technical integration dimension of RO3, operationalised across both empirical investigations rather than mapping one-to-one onto a single study.

investigations rather than mapping one-to-one onto a single study. Study 1 contributes the operational context within which implementation occurs: the 48-stratum design captures whether rtBRMS effectiveness varies systematically across gate topologies, temporal periods, day types, and flight types, identifying the contextual boundaries within which the system delivers measurable benefits and the conditions under which it does not. This information is essential for determining where implementation investment should be concentrated (Shadish, Cook and Campbell, 2002). Study 2 contributes the operator user-experience mechanisms through which organisational support translates into sustained system use: the PLS-SEM model tests whether perceived system predictability and reduced job stress predict perceived performance contribution and work engagement, which in turn predict performance, productivity, and satisfaction (Venkatesh, Brown and Bala, 2013). The integration of Study 1 and Study 2 findings in Chapter 6 therefore addresses RO3 from both the system-level perspective (under what user-experience conditions do operators accept and sustain rtBRMS use?), providing a comprehensive socio-technical understanding that neither study could deliver independently.

Gap Questions 4–5 (partial coverage, scope boundaries, and future research)

Gap Question 5 receives substantial coverage through Study 1's 4 × 3 × 2 × 2 stratification design, which captures treatment-effect heterogeneity across 48 distinct operational contexts, providing granular evidence about which combinations of spatial, temporal, day-type, and flight-type conditions amplify or attenuate rtBRMS effectiveness (Rott, Schultz and Fricke, 2023; Schultz, 2018). Study 2 further addresses Gap Question 5

through eight moderation hypotheses (S2-H10–S2-H17) testing whether passenger type, interaction frequency, level of responsibility, years of experience, operational area, role, and flights per shift moderate the strength of key structural pathways (Hair, Hult, Ringle and Sarstedt, 2022). Gap Question 4, by contrast, receives only limited coverage because both studies adopt cross-sectional designs that capture a single temporal snapshot rather than longitudinal trajectories of learning, adaptation, and institutionalisation. This limitation is acknowledged explicitly in Section 3.12 and identified as a priority for future research: a longitudinal panel design tracking the same operators and operational metrics over multiple months of rtBRMS deployment would enable the temporal-dynamic analysis that Gap Question 4 demands but that the present cross-sectional design cannot provide (Saunders, Lewis and Thornhill, 2019). This mapping ensures that every gap question identified in the literature review is traceable to a specific research objective, a specific empirical study, and a specific analytical technique, or, where coverage is partial, to an explicit acknowledgement of scope boundaries and a concrete direction for future work.

2.9 IMPLICATIONS FOR THIS RESEARCH

2.9.1 Conceptual Framework and Research Design

The literature review and gap analysis provide valuable insights for the present study. A conceptual framework has been developed that makes the relevant determinants of real-time boarding route management systems operationalizable. Guided by this framework, a literature search has been conducted across relevant domains (operational mechanisms, human factors, socio-technical implementation) which has produced a variety of approaches to parts of the underlying research objectives. At the same time, however, a review guided by the conceptual framework has shown where the gaps and weaknesses of existing approaches lie in detail.

None of the concepts presented consider all relevant determinants with regard to the underlying understanding of rtBRMS effectiveness and with the focus on operational variance reduction, operator acceptance, and sustained implementation. Likewise, the prevailing dynamics in the construct (feedback loops between operational outcomes and operator predictability, temporal evolution of work practices, contextual moderation by

operational conditions) are not sufficiently considered. The aim of this thesis is to take this holistic understanding as a basis to evaluate rtBRMS effectiveness and identify implementation requirements that enable sustained operational benefits.

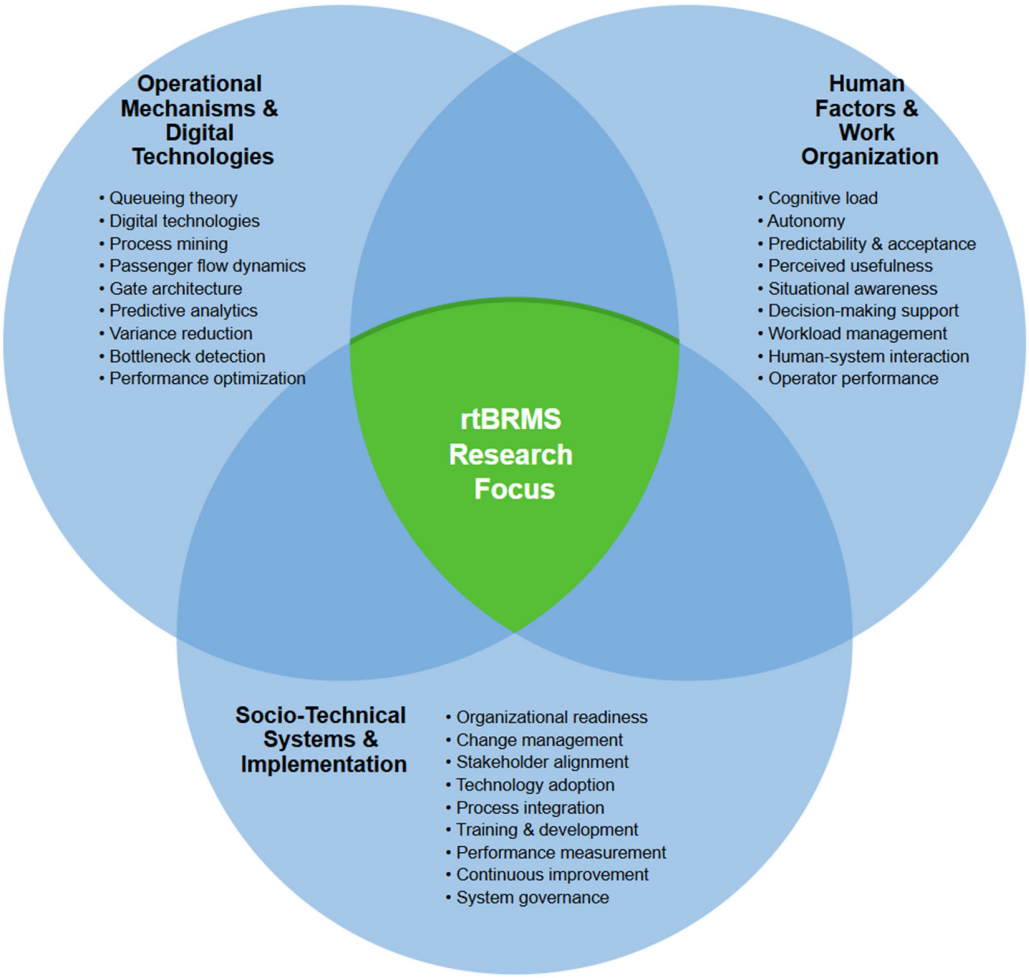


Figure 2-9 Implications of the conceptual framework for the research gap. Own illustration based on synthesis of operational mechanisms literature (Kingman, 1961; Hopp & Spearman, 2011; van der Aalst, 2016; Schultz, Rosenow and Olive, 2022), human factors research (Parasuraman & Riley, 1997; Davis, 1989; Endsley, 1995), and socio-technical systems theory (Trist & Bamforth, 1951; Kotter, 1996; Mumford, 2006).

Figure 2.9 applies the conceptual framework to illustrate the research gap that this thesis addresses. The framework shows that rtBRMS effectiveness depends on the intersection of three primary domains: Operational Mechanisms (passenger flow control, queueing dynamics, spatial constraints), Human Factors (operator predictability, situation

awareness, motivation), and Socio-Technical Implementation (stakeholder alignment, change management, performance measurement). All three domains are coloured blue to indicate that they will be considered in the data collection and analysis phases of this research. The bidirectional arrows between domains are also coloured blue to indicate that interactions and feedback loops will be explicitly examined. The central intersection, where all three domains overlap, is highlighted in green to emphasize that this is the primary focus of the research: understanding how technical capabilities, human responses, and organizational conditions jointly determine rtBRMS effectiveness.

Accordingly, a complete picture of rtBRMS effectiveness can only emerge by considering operational mechanisms (flow control algorithms, queueing dynamics, spatial constraints), human factors (operator predictability, situation awareness, cognitive load, motivation), and socio-technical implementation (stakeholder alignment, change management, performance measurement, organizational support). All determinants are hence considered in the phase of data collection to gain knowledge. The focus encompasses both operational outcomes (Gate Occupation Time variance, milestone stability, coordination effectiveness) and human-organizational responses (operator predictability, acceptance, work practice adaptation, stakeholder satisfaction).

2.9.2 Scope

It would be too broad for this work to aim to explore all domains of influence equally. The approaches presented in the corresponding sections show how diverse each individual domain is, from queueing theory and boarding optimization to predictability calibration and change management. As such, although the holistic approach is necessary to satisfy the understanding of rtBRMS effectiveness, the scope of this thesis is focused on specific aspects within each domain that are most critical to achieve the research aims.

In the operational mechanisms domain, the focus is on passenger arrival variance, Gate Occupation Time, and milestone stability rather than comprehensive turnaround optimization across all subprocess (fuelling, catering, baggage handling). In the human factors domain, the focus is on operator predictability, perceived usefulness, and situation

awareness rather than exhaustive operator user-experience profiling or personality assessment. In the socio-technical implementation domain, the focus is on stakeholder alignment, training effectiveness, and performance measurement rather than comprehensive organizational transformation or cultural change initiatives.

This focused scope enables rigorous empirical investigation of the central research gap (whether rtBRMS can achieve operational effectiveness and operator acceptance in practice) while acknowledging that broader questions about comprehensive turnaround optimization, long-term organizational transformation, and system-wide airport digitalization remain important topics for future research. The boundaries of this thesis are thus defined by the intersection of operational variance reduction, operator acceptance, and implementation feasibility, with the goal of providing actionable evidence that can inform rtBRMS deployment decisions and guide future research in this emerging domain.

The anticipated theoretical and practical contributions of this thesis are stated in Section 1.5; their realised form, evidenced by Studies 1 and 2, is reported in Chapter 7.

2.10 RESEARCH GAPS AND IMPERATIVES FOR THIS STUDY

The research gaps identified in the preceding sections are corroborated and reinforced by recent research programmes, funding initiatives, and scholarly agendas across multiple high-impact domains, airport operations, human factors in automation, and socio-technical systems implementation. This section synthesises these converging imperatives to demonstrate that the gaps addressed by this thesis are not merely theoretical observations but are recognised as critical priorities by the international research community.

2.10.1 The Execution-Control Gap in Airport Operations

The evolution from monitoring to prediction in airport operations has exposed a fundamental limitation: predictive systems cannot prevent the operational variability they forecast (Rott, Schultz and Fricke, 2023; Tang et al., 2025). Recent research explicitly calls

for a paradigm shift toward execution-layer interventions that actively regulate flow rather than merely observing or anticipating disruptions.

Recent operational-research scholarship articulates this need directly, calling for interdisciplinary research that anticipates the future demands of a rapidly evolving global aviation landscape and that prioritises the optimisation of passenger and baggage flow through integrated technological and organisational solutions (Evler et al., 2022; Tang et al., 2025).

Tuduriu et al. (2025), in their Critical Minute Theorem study, demonstrate that turnaround delays are not random but structurally determined, and that early recognition and intervention at critical minutes can significantly reduce propagated delays. Their work calls for research that moves beyond predictive analytics toward deterministic, algebraic frameworks that identify fragility points in real time. This aligns precisely with the present study's focus on rule-based, real-time flow control that constrains variance at source rather than reacting to its consequences.

Rott, Schultz and Fricke (2023) document that, despite advanced predictive capabilities, persistent data-quality issues, irregular milestone adherence, and coordination fragilities undermine the reliability of Target Off-Block Time (TOBT) assignments. Their analysis reveals that 60–70% of turnaround-time variance originates in boarding and deboarding phases, precisely the domain where real-time passenger-flow control can deliver maximum impact. The authors call for research that integrates event-log systems with execution-layer control mechanisms capable of acting on discovered patterns in real time, creating closed-loop feedback between monitoring and actuation.

2.10.2 The Human Factors Gap in Airport Automation

Calls in the human-automation literature reinforce this need. Research on aviation automation acceptance (Lee and See, 2004; Parasuraman and Riley, 1997; Endsley, 2017) consistently identifies operator predictability calibration, perceived usefulness, and work engagement as critical moderators of system effectiveness, particularly during the

integration of autonomous and semi-autonomous systems into safety-sensitive operational ecosystems. This thesis responds directly to that call by investigating ground-handler perceptions, predictability formation, and acceptance determinants in the rtBRMS context.

The broader human factors literature echoes this need. Cross-domain reviews of transport-sector automation note that systematic comparative research on lessons learned across road, aviation, maritime, and rail is still limited, and that automation maturity differs markedly across modes (Schultz, 2018). This calls for cross-domain research that can inform airport-specific automation design. This interdisciplinary perspective aligns with the present study's integration of manufacturing flow control principles, human-automation interaction theories, and aviation-specific operational constraints.

Methodological calls in the technology-acceptance literature highlight a recurrent gap: prior research has often relied on single theoretical models, overlooking the complex interplay of user-experience, social, and environmental factors that influence acceptance (Venkatesh, Brown and Bala, 2013; Sykes, Venkatesh and Gosain, 2009). This thesis responds with a multi-framework approach that integrates the Technology Acceptance Model 2 (Venkatesh and Davis, 2000), the Job Demands–Resources model (Bakker and Demerouti, 2007), human–automation interaction theory (Lee and See, 2004), and the Information Systems Success model (DeLone and McLean, 2003) to capture the multifaceted nature of operator acceptance under rtBRMS.

2.10.3 The Socio-Technical Integration Gap

The socio-technical systems literature consistently emphasizes that technological innovations achieve sustained effectiveness only when aligned with organizational structures, work practices, and human capabilities (Trist and Bamforth, 1951; Mumford, 2006; Clegg, 2000). Recent research calls extend this principle specifically to airport digital transformation contexts.

Recent socio-technical scholarship on airport digital transformation (Pasmore et al., 2019; Winby and Mohrman, 2018; Schultz and Fricke, 2011) calls for integrated research

agendas that address human-automation teaming, real-time machine learning in operations, and governance for data interoperability. Such work emphasises that airport digital transformation, when approached primarily through technological integration and data-driven optimisation, provides limited insight into system-level reasoning and governance. This call for integrated socio-technical research directly supports the present study's investigation of how rtBRMS implementation must account for ground-handling work organisation, coordination protocols, and stakeholder alignment to achieve operational effectiveness.

Research on airport digital maturity and transformation (Halpern and Mwesiumo, 2021; Lee and Yu, 2018) identifies critical gaps in understanding how airports can navigate complex, high-growth environments and convert operational challenges into opportunities through strategic technological investment. This literature calls for research that moves beyond isolated technological solutions toward enterprise-level digital architectures capable of predictive planning and dynamic response management, a vision that requires understanding not only technical capabilities but also organisational readiness, change-management processes, and performance-measurement frameworks.

The challenge of socio-technical integration is particularly acute in ground handling operations, where multiple stakeholders (airlines, ground handlers, airport authorities, air traffic control) must coordinate under time pressure and operational uncertainty. Research on A-CDM implementation (Halpern and Mwesiumo, 2021; Lee and Yu, 2018) notes that stakeholders frequently work side-by-side but in functional silos, calling for research that can bridge coordination gaps through both technological and organisational interventions. This aligns with the present study's investigation of how rtBRMS can formalize coordination while preserving operator flexibility and autonomy.

2.10.4 The Variance-Reduction and Process-Reliability Gap

The operations management literature has long emphasized that variance reduction at source delivers disproportionately larger benefits than downstream intervention (Hopp

and Spearman, 2011; Goldratt, 1984). Recent airport operations research explicitly calls for application of these principles to turnaround processes.

Schultz and Fricke's (2011) work on turnaround reliability frames the SESAR 2020 performance target of compressing turnaround toward 15 minutes while increasing process reliability. This ambitious goal cannot be achieved through coordination and prediction alone; it requires fundamental changes in how passenger flows are regulated and how spatial interference is prevented. The authors call for research that can overcome the deficiencies of currently applied buffer strategies for ground processes through proactive flow control rather than reactive buffering.

Research on delay propagation in airport networks (Pyrgiotis et al., 2013; Fleurquin, Ramasco and Eguíluz, 2013) demonstrates that small local disturbances generate non-linear, system-wide disruptions when turnaround operations lack robust control mechanisms. The study calls for novel simulation-optimisation approaches that allow multiple service providers to build robust plans for their teams independently while supporting overall coordination through central scheduling of all involved turnaround activities. This vision of distributed yet coordinated control aligns precisely with rtBRMS capabilities for rule-based passenger release that respects both operational constraints and stakeholder autonomy.

The Critical Minute Theorem research (Tuduriu et al., 2025) explicitly calls for a paradigm shift in how turnaround variability is conceptualised and managed, redefining the operator's role from corrective to counter-perturbative action and treating operational disruptions as structurally anticipated rather than merely managed. This call for anticipatory, structure-based control rather than reactive firefighting validates the present study's emphasis on upstream flow regulation as a variance-reduction mechanism.

2.10.5 The Empirical Validation Gap

The aviation operations literature has accumulated a striking volume of theoretical, simulation-based, and laboratory evidence that field validation has not caught up with, and

the imbalance has consequences the field has been slow to acknowledge. Three are particularly damaging. Simulation-based studies routinely assume agent compliance, simplified geometries, and stationary demand, none of which survives contact with live operations; the 20 to 40% reductions repeatedly cited from this work (Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015) are upper bounds that the field has come to treat as expectations. Laboratory studies of automation acceptance and human-automation interaction (Lee and See, 2004; Endsley, 2017) generalise from low-stakes deliberation contexts to safety-sensitive real-time work without empirical warrant. And the institutional reports that anchor much of the A-CDM literature (Eurocontrol, 2017; SESAR Joint Undertaking, 2016) report aggregate before-after gains without quasi-experimental controls, leaving causal attribution unresolved. The field therefore operates on an evidence base that is technically extensive but inferentially weak; what is missing is not more theory or more simulation but stratified field evidence collected under authentic heterogeneity, which is precisely what the 48-stratum design of Study 1 supplies.

Research on passenger-flow management (Anagnostopoulou et al., 2024; Oprea et al., 2024) emphasises the importance of real-world implementation and performance analysis, noting that many proposed solutions remain untested under authentic operational conditions. The study calls for research that can demonstrate not just technical feasibility but also operational viability, stakeholder acceptance, and sustained effectiveness across diverse airport contexts.

The turnaround operations literature consistently emphasises that efficient boarding procedures must account for both operational constraints and individual passenger behaviour (Schultz, 2017), and that, in contrast to fuelling, catering, and cleaning (which are driven by ground staff), the boarding process is driven primarily by the passenger rather than by airport or airline employees (Schultz, 2018). This observation underscores the need for research that investigates how automated flow control systems interact with human behaviour, organizational practices, and operational variability in real-world settings, precisely the focus of the present study's field implementation and stakeholder evaluation.

2.10.6 Integration and Positioning of This Research

The research calls synthesised above converge on a common imperative: the need for integrated research that bridges operational mechanisms, human factors, and socio-technical implementation to address the prediction-execution gap in airport operations. Although prior work has begun to address each of these strands in isolation, no single study has combined them into a coherent execution-layer investigation. The present research directly responds to these calls along five interlocking axes:

1- Operational innovation. It implements and evaluates a real-time, rule-based passenger-flow control mechanism (rtBRMS) that moves beyond prediction towards execution, addressing the explicit call for upstream flow-control mechanisms that constrain variance at source. Existing A-CDM and turnaround research has demonstrated the predictive potential of digital integration but has consistently stopped short of execution control (Eurocontrol, 2017). Recent prediction-oriented studies of turnaround duration and off-block delay (De Falco et al., 2023; Falque, Mazure and Tabia, 2024; Luo et al., 2022; Evler et al., 2022) explicitly position their contributions as monitoring rather than regulation, leaving the execution layer underexamined.

2- Human-factors integration. It systematically investigates operator user-experience mechanisms, perceived system predictability, autonomy preservation, comparative superiority, and work engagement, as critical conditions for the effectiveness of automation, responding to long-standing calls for frameworks that account for the interplay of cognitive, motivational, and organisational factors (Bainbridge, 1983; Endsley, 1995, 2017). The decision to ground these constructs in established theories of human-automation interaction, work engagement, and technology acceptance (Bakker and Demerouti, 2007; Davis, 1989) extends the human-factors lens that earlier turnaround and boarding studies have largely treated as an exogenous given (Bachmat et al., 2006, 2009; Ferrari and Nagel, 2005; Jaehn and Neumann, 2015).

3- Socio-technical perspective. It examines how rtBRMS implementation must align with ground-handling work organisation, coordination protocols, and stakeholder dynamics, addressing calls for research that bridges technological capability with organisational

readiness and change management (Eurocontrol, 2017; ICAO, 2019). This reading of airport operations as a socio-technical system, rather than a purely engineered queueing system, complements operational analyses of passenger boarding rates and gate-area dynamics (Kobbaey and Bilquise, 2023) by adding the organisational-coordination layer they identify as a residual gap.

4- Empirical validation in live operations. It conducts field research in authentic operational environments to demonstrate not only technical feasibility but also practical effectiveness, stakeholder acceptance, and sustained performance improvements. Prior turnaround research has been dominated by simulation, queueing-network modelling, and retrospective delay analyses (Bachmat et al., 2006; Fricke and Schultz, 2009; Kobbaey and Bilquise, 2023; Luo et al., 2022); the small number of live-environment studies has typically reported descriptive rather than experimentally controlled evidence (Gehlen and Ronzani, 2025). The present 48-stratum field experiment therefore addresses a genuine deficit in audit-traceable, condition-controlled evidence.

5- Theoretical advancement. It integrates queueing theory (Kingman, 1962; Kleinrock, 1975; Little, 1961, 2011), human-automation interaction frameworks (Endsley, 2017), the Job Demands–Resources model (Bakker and Demerouti, 2007), and information systems success theory (Davis, 1989) into a single explanatory architecture that links variance reduction at the gate chokepoint with operator user-experience conversion mechanisms. This cross-domain integration responds to the recurring critique that operational and behavioural strands of airport research remain methodologically segregated (Endsley, 2018; Evler et al., 2022; Halpern and Mwesiumo, 2021).

By addressing these interconnected research calls, the study contributes to closing the gap between the theoretical potential and the practical implementation of real-time flow-control systems in airport operations. It provides empirical evidence, implementation guidance, and theoretical insights that advance both academic understanding and practical deployment of execution-layer automation in complex, human-centric operational environments.

2.11 CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

2.11.1 Study 1: Operational Hypotheses (S1-H1–S1-H6b)

The theoretical framework in this study establishes that passenger-flow variability constitutes the dominant source of stochastic delay in short-haul turnarounds and that real-time, rule-based flow regulation, as implemented in the rtBRMS, directly targets the mechanisms that generate congestion at gates, airbridges and aisles. The dependent variables examined in this study (GOT, boarding/deboarding windows, throughput, high-performance boarding indicator (≤ 13 min), high-performance deboarding indicator (≤ 11 min); see Table 3) quantify the operational consequences of precisely these micro-level queueing phenomena. Because rtBRMS represents a flow-execution intervention, not a predictive system nor a static boarding policy, its causal effects should be observable in KPIs sensitive to the timing, stability and rate of passenger movement. The hypotheses formulated below therefore translate the theoretical mechanisms of queueing, TOC, and A-CDM into empirically testable statements about how rtBRMS influences the flight-level performance metrics.

Hypotheses Development and Alignment with ROs

The hypotheses in Study 1 are derived directly from the research objectives that guide this thesis. RO1 requires quantification of the effect of rule-based flow-control automation on Gate Occupation Time, boarding and deboarding windows, throughput, and fast-process thresholds in live operations. Each hypothesis below operationalises a specific facet of RO1 by translating the theoretical mechanisms identified in the literature review, queueing-theoretic variance compression (Kingman, 1961; Little, 1961), Theory of Constraints bottleneck management (Goldratt, 1984), and A-CDM milestone reliability (Gehlen and Ronzani, 2025), into directional predictions about the KPIs specified in RO1. The hypothesis set is structured to cover the full scope of RO1: S1-H1 addresses total ground time (GOT), S1-H2a/S1-H2b address the temporal windows of the two passenger-movement phases, S1-H3 addresses flow efficiency (throughput), S1-H4 tests whether architectural complexity moderates the intervention effect, S1-H5 examines robustness across load conditions, and S1-H6a/S1-H6b test whether rtBRMS shifts the probability of meeting operationally critical fast-process thresholds. Together, these six

main hypotheses, subdivided into eight directional tests (S1-H1, S1-H2a, S1-H2b, S1-H3, S1-H4, S1-H5, S1-H6a, S1-H6b), provide a comprehensive empirical test of the causal mechanism linking real-time flow-control automation to queue-sensitive turnaround performance.

2.11.1.1 Effect of rtBRMS on Gate Occupation Time (GOT)

Extensive research shows that boarding-induced variability propagates non-linearly into total ground time, as cycle-time inflation in serial processes is governed by the slowest and most variable stage (Steffen and Hotchkiss, 2012; Schultz, 2018). Since passenger-flow congestion at doors, tunnels and aisles dominates this bottleneck in short-haul rotations, any intervention that reduces arrival variance, stabilizes WIP, and prevents queue spillback should materially shorten Gate Occupation Time (Little, 1961; Kingman, 1961). Moreover, A-CDM evidence indicates that increased milestone reliability (e.g., stable TOBT) is strongly associated with improved departure punctuality (Gehlen and Ronzani, 2025). By algorithmically pacing inflow and governing door-state transitions using live congestion signals, rtBRMS operationalizes the variance-reduction mechanisms prescribed by queueing theory and TOC, implying a systematic contraction of Gate Occupation Time under real operational conditions.

The expectation that rtBRMS will reduce Gate Occupation Time arises from its direct influence on the most volatile component of the turnaround process, the boarding-phase bottleneck. Queueing theory makes clear that when variability is suppressed at a system's slowest station, the downstream cycle-time contraction propagates throughout the entire serial chain (Little, 1961; Kingman, 1961). Because rtBRMS intervenes precisely at the points where burstiness forms (door thresholds, shared tunnels, and aisles) it transforms inherently unstable inflow patterns into regulated, predictable streams. In short-haul operations, where boarding inefficiencies rapidly magnify into cumulative delay, stabilizing these early flows produces a knock-on harmonization of subsequent handling stages. This prediction is further supported by empirical turnaround research demonstrating that boarding-phase delays exceeding 10 minutes occur in 15–25% of short-haul operations and propagate through tightly coupled flight schedules, generating

network-wide punctuality degradation (Evler et al., 2022; Rott, Schultz and Fricke, 2023). Process-mining analyses of turnaround event logs confirm that milestone predictability depends on the stability of upstream flow processes, with persistent variability undermining even mature A-CDM governance regimes (Rott, Schultz and Fricke, 2023). Thus, from a theoretical standpoint, reductions in GOT naturally follow from reducing flow irregularity at the bottleneck most responsible for system-wide temporal inflation. Therefore, this study proposes the following hypothesis.

S1-H1. rtBRMS reduces Gate Occupation Time relative to legacy coordination.

2.11.1.2 Effect of rtBRMS on Boarding and Deboarding Windows

Prior controlled experiments consistently demonstrate that structured sequencing reduces temporal dispersion in boarding times (Moreira et al., 2023). Queueing theory further predicts that reducing variance in interarrival and service processes yields disproportionate reductions in waiting times (Kingman, 1961; Whitt, 1993). Because rtBRMS acts directly on these variance-generating mechanisms, by smoothing inflow, preventing burstiness, and maintaining aisle clearance, it should shorten both the Board Window and Deboard Window, thereby improving the temporal regularity of passenger movement. Given that boarding constitutes the primary bottleneck in short-haul operations, effects on the boarding window should be particularly pronounced.

Boarding and deboarding windows represent the micro-temporal signatures of passenger-flow stability, making them especially sensitive to upstream regulation. When arrival patterns are erratic, the aisle behaves as a constrained stochastic service facility prone to cascading interference events; this elongates the effective window over which boarding and deboarding unfold. By contrast, rtBRMS is designed to transform what would otherwise be a burst-dominated arrival process into a paced, geometry-aware flow regime. Under such conditions, the spatial choreography within tunnels and aisles becomes smoother, seat-interference events diminish, and the natural rhythm of movement accelerates. Discrete-event simulations confirm that structured boarding strategies can reduce boarding duration by 10–20% under controlled conditions (Steffen and Hotchkiss,

2012; Moreira et al., 2023), while field studies demonstrate that deboarding can progress up to approximately 50% faster than boarding when flow is uninterrupted but deteriorates sharply under localised bottlenecks (Schultz, 2017). Theoretically, this translates into more compact boarding and deboarding windows because the system stops absorbing shocks from variability and instead operates in a state of controlled flow equilibrium. Therefore, this study proposes the following hypothesis.

S1-H2. rtBRMS reduces (H2a) Board Window and (H2b) Deboard Window relative to legacy conditions.

2.11.1.3 Effect of rtBRMS on Throughput (pax/min)

Throughput is an intensive measure of flow efficiency, directly reflecting system capacity under stochastic demand. Studies on synchronized resource allocation show that harmonizing entry timing with downstream capacity increases achievable pax/min rates (Falque, Mazure and Tabia, 2024; Gehlen and Ronzani, 2025). Machine-learning analyses further indicate that readiness and sequencing are among the strongest predictors of deboarding and boarding rates (Okwir, Amouzgar and Ng, 2025; Yuan, Wang and Lai, 2025). Because rtBRMS employs real-time pacing and topology-aware routing, which eliminate burst arrivals, mitigate tunnel-flow conflicts, and maintain aisle service rates, it should systematically increase boarding throughput (pax/min) and deboarding throughput (pax/min).

Throughput, conceptually, is a direct expression of how efficiently a system converts potential movement into actual movement under constraints of space and time. In congested passenger-handling environments, throughput falters when uncoordinated arrivals exceed the aisle's capacity to process them without obstruction. rtBRMS changes this dynamic by aligning inflow timing with the physical and temporal constraints inherent to the aircraft interior. Hopp and Spearman's (2011) Factory Physics framework formalises this relationship: throughput in a serial system is maximised when work-in-process is maintained at the level that balances utilisation against congestion, and any intervention that reduces arrival variance moves the system closer to this optimal operating point. In the

rtBRMS context, pacing and door-state governance regulate the rate at which passengers enter the constrained aisle environment, preventing the WIP accumulation that degrades throughput under uncontrolled conditions. As pacing, routing, and door-state governance reshape how passengers engage with shared access points, the aisle's latent processing capability is unlocked. Instead of being saturated by variability, the system begins to operate near its natural service frontier, enabling higher passenger-per-minute rates. From a theoretical standpoint, higher throughput is thus not an incidental benefit but a predictable consequence of coordinated flow harmonization. Therefore, this study proposes the following hypothesis.

S1-H3. rtBRMS increases boarding and deboarding throughput (pax/min) relative to legacy coordination.

2.11.1.4 Moderation by Architectural Complexity (Gate Type)

Architectural complexity, particularly in shared or multi-access gate tunnels, introduces additional coordination costs, conflict points and route-interference patterns that degrade passenger-flow performance (Pellegrini, Castelli and Pesenti, 2017; Rott, Schultz and Fricke, 2023). Because rtBRMS explicitly coordinates more than 60 door/access nodes in real time, with topology-aware routing rules that eliminate human-error events and resolve cross-stream interference, the magnitude of its effect should increase with gate complexity. As it has been found that performance heterogeneity is highest in shared-access infrastructures, it could be expected that the marginal gains produced by algorithmic flow control are largest where legacy coordination performs poorest.

Its effects therefore scale with the structural demands of the environment. As architectural complexity increases (through multi-access tunnels, shared-area geometries, and interacting passenger streams) interference effects, queue spillback, and stochastic congestion intensify, amplifying the weaknesses of reactive, manual coordination (Orhan and Orhan, 2020; Oprea et al., 2024). Empirical and simulation-based research shows that human operators struggle to anticipate and resolve emergent conflicts in such

environments, as spatial dependencies and passenger interactions generate non-linear propagation of delay (Schultz, 2017; Schultz and Reitmann, 2018).

This moderation hypothesis addresses the boundary-condition dimension of RO1 by testing whether the operational benefits of rtBRMS are uniform across gate architectures or scale with infrastructure complexity. The theoretical rationale draws on both queueing theory, which predicts that variance amplification is strongest in systems with multiple interacting service stations (Whitt, 1993), and human-factors research demonstrating that manual coordination degrades disproportionately under spatial complexity (Wickens et al., 2015). Conversely, studies demonstrate that structured, algorithmic or AI-driven flow management delivers disproportionately larger performance gains in topologically complex gate systems, precisely because congestion-sensitive pacing and rule-based routing suppress the variance amplification inherent in these layouts (Moreira et al., 2023). The more complex the gate architecture, the more value is created by replacing reactive human decision-making with proactive, system-guided coordination.

S1-H4. The effect of rtBRMS on GOT (min) is amplified at higher levels of architectural complexity relative to simpler gates.

2.11.1.5 Robustness Across Load Conditions and Temporal Bands

Queueing systems deteriorate non-linearly under high utilization: as passenger load increases, variability amplification becomes stronger, increasing congestion depth and persistence (Pyrgiotis et al., 2013). However, interventions that stabilize WIP and regulate inflow can counteract this nonlinear growth, producing benefits that scale with load. Therefore, although rtBRMS should reduce GOT across all demand conditions, absolute time savings are expected to be slightly larger at high loads. Forecasting research similarly shows that process-time variance tends to be load-invariant once corrective mechanisms are in place (Mori, 2024; Okwir, Amouzgar and Ng, 2025).

Load conditions exert a nonlinear influence on system stability, with higher passenger volumes amplifying even small disruptions into significant temporal distortions.

Queueing systems under stress tend to accumulate variance, producing longer and less predictable processing times. Flow-stabilizing interventions like rtBRMS counteract this tendency by enforcing regularity precisely at those points where instability would otherwise emerge. Kingman's (1961) G/G/1 approximation formalises this non-linearity: expected waiting time scales with the sum of squared coefficients of variation in arrival and service times, meaning that even modest reductions in arrival variance yield disproportionately large reductions in waiting time as utilisation approaches capacity. This non-linear relationship explains why flow-control interventions at gate chokepoints produce outsized operational benefits under peak-load conditions, directly addressing the load-sensitivity dimension of RO1. Consequently, while the system should exhibit improvements regardless of load, theoretical models suggest that the benefits intensify under heavier passenger densities. At higher loads, each unit of variance suppression yields a greater marginal improvement, as the system is steered away from the steep portion of the congestion curve and back toward its stable operating region. Therefore, this study proposes the following hypothesis.

S1-H5. rtBRMS reduces GOT (min) across all passenger-load levels and temporal bands, with larger absolute reductions at higher loads.

2.11.1.6 Effect of rtBRMS on Fast-Process KPIs (Binary Outcomes)

Binary fast-process KPIs (high-performance boarding indicator ≤ 13 min; high-performance deboarding indicator ≤ 11 min) are sensitive to the stability of passenger flow and to the absence of disruption in door, tunnel and aisle operations. Because rtBRMS eliminates burst arrivals, enforces rule-governed door sequencing, and resolves shared-area conflicts, it should increase the probability of achieving these standards. Previous work shows that punctuality KPIs are highly responsive to small improvements in process-time predictability (Moreira et al., 2023). As it has been found that stable queueing environments improve milestone adherence, it could be expected that rtBRMS will produce measurable gains in the probability of meeting fast-process thresholds.

Fast-process KPIs capture the binary question of whether a system performs within an operationally desirable threshold under real-world variability. Because these KPIs hinge on maintaining uninterrupted passenger movement, they are highly responsive to the micro-level stability that rtBRMS seeks to impose. When dwell times (i.e., the duration passengers spend stopped in the aisle while stowing luggage or preparing to sit), cross-flow conflicts (situations in which boarding and deboarding passengers intersect and block one another's movement), and aisle blockages (queues that form when passengers accumulate faster than they can move forward) are minimized, the system is far more likely to complete boarding and deboarding quickly enough to satisfy these rigid performance benchmarks.

Theoretically, the rtBRMS reduces the frequency and duration of these micro-level disruptions, shifting the distribution of process times away from the variability-inflated tail and toward a region where fast-process completion becomes substantially more probable. In this sense, improvements in the high-performance boarding indicator (≤ 13 min) and the high-performance deboarding indicator (≤ 11 min) are not accidental outcomes but reflect a more predictable, variance-controlled flow environment produced by the system's rule-based routing. These binary KPIs are particularly important for addressing RO1 because they translate the continuous improvements in flow stability into operationally meaningful thresholds that directly determine whether a turnaround meets the performance standards required for schedule integrity and network punctuality (Evler et al., 2022; Gehlen and Ronzani, 2025). Therefore, this study proposes the following hypotheses.

S1-H6a. rtBRMS increases the probability that flights meet the high-performance boarding threshold (≤ 13 min).

The literature shows that boarding duration is highly sensitive to inflow variability, aisle interference, and passenger-arrival burstiness (Moreira et al., 2023; Schultz, 2017). Empirical boarding analyses further demonstrate that stabilizing inter-arrival patterns, reducing seat-interference events, and enforcing orderly flow can shift the distribution of boarding times toward substantially shorter durations (Schultz and Reitmann, 2018). Consequently, an intervention like rtBRMS, designed to suppress variance at door, tunnel,

and aisle chokepoints, should materially increase the likelihood of achieving the ≤ 13 min performance benchmark.

S1-H6b. rtBRMS increases the probability that flights satisfy the high-performance deboarding threshold (≤ 11 min).

Academic studies consistently find that deboarding is typically faster and less variable than boarding, yet remains susceptible to congestion effects, aisle blockages, and door-flow disturbances (Schultz, 2017; Schultz and Reitmann, 2018). Research also shows that deboarding can progress up to ~50% faster than boarding when flow is uninterrupted, but deteriorates sharply under localized bottlenecks (Schultz, 2017). Because rtBRMS mitigates these congestion drivers by regulating passenger release, enforcing conflict-free routing, and maintaining aisle clearance, it should systematically increase the probability that deboarding completes within the ≤ 11 min threshold.

Together, the six hypothesis groups in Study 1 (S1-H1 – S1-H6b) provide a comprehensive empirical test of the causal mechanism linking real-time flow-control automation to queue-sensitive turnaround performance, directly addressing RO1. The hypotheses progress systematically from the aggregate outcome (GOT in S1-H1), through the constituent temporal phases (boarding and deboarding windows in S1-H2a/S1-H2b), to the intensive flow-efficiency measure (throughput in S1-H3), and then examine boundary conditions (architectural complexity in S1-H4, load sensitivity in S1-H5) and operationally critical binary thresholds (S1-H6a/S1-H6b). This structure ensures that the empirical evidence generated by Study 1 covers the full scope of RO1, not only whether rtBRMS improves turnaround performance, but how, where, and under what conditions these improvements manifest. The findings from Study 1 also provide the operational foundation for Study 2, which investigates the operator user-experience mechanisms through which operators perceive and respond to the stabilised flow conditions that Study 1 quantifies, thereby addressing RO2.

2.11.2 Study 2: Conceptual Model and Construct Definitions

Perceived System Predictability (PSP)

Predictability is central to human reliance on automation: consistent, transparent behavior lets operators calibrate trust accurately (Lee and See, 2004) and build mental models that lower workload and vigilance demands (Parasuraman and Riley, 1997; Wickens et al., 2015). In TAM2, predictability strengthens result demonstrability and clarifies attribution, raising perceived usefulness (Venkatesh and Davis, 2000; DeLone and McLean, 2003). In airport service contexts, predictable processes correlate with higher satisfaction and lower stress (Bezerra and Gomes, 2015; Halpern and Mwesiumo, 2021). For gate operators, predictability shifts the role from reactive firefighting to proactive coordination (Endsley, 2017), simultaneously sharpening cognition and stabilizing attitudes toward the human-system partnership.

Perceived Autonomy (AUT)

Autonomy is a robust job resource in JD-R (Bakker and Demerouti, 2007), enabling operators to structure tasks, adjust sequences, and buffer disruptions. In dynamic gate environments, it allows staff to integrate system recommendations with situational judgement, adapting to local conditions rtBRMS may not capture, such as passenger assistance, equipment faults, or last-minute gate changes (Parasuraman and Riley, 1997). JD-R conceptualizes autonomy along two pathways: as a resource supporting competence and ownership that sustains intrinsic motivation, and as a buffer against demands, enabling operators to modulate pace and deploy coping strategies (Karasek, 1979). Autonomy also fosters predictability through "operator-driven situation awareness" (Endsley, 2017), creating a positive feedback loop. In rtBRMS-supported operations, this manifests as micro-sequencing within the system framework: when to communicate with crew, coordinate handlers, or override recommendations during emergencies. Such discretion ensures rtBRMS functions as decision-support enhancing capability rather than rigid automation (Lee and See, 2004), increasing engagement and reducing strain (Schaufeli et al., 2002).

Job Stress Reduction (JSR)

High-demand boarding environments expose staff to temporal pressure, crowding, and disturbance variability. JD-R theory holds that reducing demands frees cognitive and emotional resources for productive behavior (Demerouti et al., 2001; Bakker and Demerouti, 2007), while the transactional model frames stress as the appraisal that demands exceed coping resources (Lazarus and Folkman, 1984). In gate operations, key stressors are temporal pressure, congestion, coordination complexity, and disruption variability (Schultz, 2018; Kim, Barnhart and Clarke, 2017). rtBRMS reduces these by pacing inflow to prevent crowding (Hopp and Spearman, 2011), automating topology-aware routing (Steffen and Hotchkiss, 2012), and stabilizing flow to limit cascades (Evler et al., 2022). Excessive queueing and disruption are strong negative predictors of staff morale (Halpern and Mwesiumo, 2021; Bezerra and Gomes, 2015, 2016), creating a vicious cycle where congestion breeds stress that further impairs coordination. Breaking this cycle shifts operators from reactive firefighting to sustained, engagement-driven work (Bakker and Demerouti, 2007).

Perceived Performance Contribution (PPC)

PPC reflects operators' belief that the system improves their performance, corresponding to perceived usefulness in TAM2 (Venkatesh and Davis, 2000). It occupies the model's central position, translating observations of predictability, stability, and stress reduction into evaluative judgement that drives engagement and satisfaction. The IS Success Model (DeLone and McLean, 2003) positions perceived usefulness as the construct through which system quality is converted into satisfaction. PPC formation depends on result demonstrability, output quality, and job relevance: operators see smoother flows, accurate pacing, and direct relevance to passenger management. Comparable findings appear in flight-deck and ATM decision-support research (Parasuraman and Riley, 1997).

Work Engagement (ENG)

Work engagement is "a positive, fulfilling, work-related state of mind characterised by vigour, dedication, and absorption" (Schaufeli et al., 2002), distinguishing it from satisfaction, commitment, and workaholism. JD-R's motivational pathway links job resources to performance via engagement (Bakker and Demerouti, 2007), and Christian, Garza and Slaughter's (2011) meta-analysis confirms strong effects on task ($\rho = .43$) and contextual performance. rtBRMS features, real-time feedback, transparent logic, preserved discretion, match those shown to enhance engagement in ERP and automation contexts (Sykes, 2015). By absorbing demands through automated stabilisation, rtBRMS frees cognitive capacity (Hobfoll, 1989) for engaged execution, measured via the validated UWES-3 (Schaufeli et al., 2017).

Individual Work Performance (IWP)

IWP captures behaviors and actions relevant to organizational goals. The IWPQ has strong construct validity and reliability across occupational groups (Koopmans et al., 2013). Engagement, perceived contribution, and system support are recognized antecedents of higher IWP in digital and operational environments. Content and face validity were established before data collection following the procedures specified in Section 4.3.1 (Hair et al., 2022).

In airport operations, higher IWP strengthens turnaround reliability because task-level execution is tightly coupled with timing and accuracy of gate processes. Disruptions during boarding (mis-sequencing, miscommunication, delayed actions) create ripple effects propagating through the chain (Schultz, 2018). High IWP reduces these disruptions through more consistent procedural timing, quicker resolution of micro-bottlenecks, and fewer execution errors (de Treville, Shapiro and Hameri, 2014). Operators with higher attentional control, accuracy, and proactive coordination reduce delays by maintaining clearer communication and stronger situation awareness (Endsley, 2018; Wickens et al., 2015). Higher IWP improves the operator's task reliability and enhances system-level performance by minimizing variability and reducing cascading errors.

Employee Productivity (EMP)

EMP captures perceived output, handling efficiency, and throughput, the quantity dimension complementing IWP's quality focus (Campbell and Wiernik, 2015). In the IS Success Model, productivity is positioned as a downstream net benefit reached through perceived usefulness (DeLone and McLean, 2003). Productivity gains in gate operations come from waste elimination, waiting, rework, congestion-induced idleness, not faster work (Hopp and Spearman, 2011; Evler et al., 2022). By stabilizing flow, rtBRMS frees time for productive activity. Perceived measurement is used given the cross-sectional design and attribution challenges in multi-stakeholder settings (Goodhue and Thompson, 1995). PPC drives EMP motivationally; IWP drives it operationally; both are necessary (Bakker and Demerouti, 2007).

System Satisfaction (SS)

System satisfaction represents a holistic evaluation of reliability, usefulness, ease of coordination, and contribution to effective work. Satisfaction is strongly influenced by stability, clarity, and predictability (Bezerra and Gomes, 2015), and reduced by service failures and disruptions (Halpern and Mwesiumo, 2021). In the IS Success Model, satisfaction is the highest-order attitudinal response in which users synthesize evaluations of system quality, information quality, and realized benefits into a single global judgement (DeLone and McLean, 2003). It integrates cognitive signals (predictability, reliability, clarity) and affective responses (ease of use, reduced strain) (Petter, DeLone and McLean, 2005). Satisfaction is strongly influenced by the degree to which interactions enable users to achieve goals with minimal friction, lower errors, and improved stability (Goodhue and Thompson, 1995). In airport settings, satisfaction captures operators' overall appraisal of whether rtBRMS performs reliably, supports their work, enhances productivity, and reduces volatility. It is therefore the final attitudinal outcome, integrating upstream user-experience, cognitive, motivational, and performance effects.

Contextual Moderators

Airport operations vary across gate architecture, passenger composition, operator roles, experience, and workload. Contextual features influence both process evaluations and performance dynamics (Bezerra and Gomes, 2015; Fodness and Murray, 2007;

Halpern and Mwesiumo, 2021). The model incorporates single-indicator formative moderators (role, flights per shift, passenger type, operational area, interaction frequency, experience), analyzed using the two-stage PLS-SEM procedure (Hair et al., 2019).

Synthesis and Proposed Structural Model

The framework integrates: queueing theory and factory physics (Kingman, 1961; Hopp and Spearman, 2011) for variance suppression that compresses windows, creating the operational stability operators perceive; human-automation theory (Lee and See, 2004; Parasuraman and Riley, 1997) for how transparent behavior enables reliance calibration, forming the cognitive substrate of PSP; JD-R (Bakker and Demerouti, 2007; Demerouti et al., 2001) for dual motivational pathways through which resources (autonomy, predictability) and reduced demands (stress reduction) independently enhance ENG; TAM2 (Venkatesh and Davis, 2000; Davis, 1989) for cognitive instrumental processes (result demonstrability, output quality, job relevance) through which predictability translates into PPC; the IS Success Model (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008) positioning SS as the highest-order outcome integrating all signals; and validated performance frameworks distinguishing IWP (task-level quality) from EMP (shift-level throughput) (Koopmans et al., 2013; Chatterjee, Chaudhuri and Vrontis, 2022; Ashraf, 2020).

Despite the richness of these traditions, no prior work has combined them into a single empirically tested model explaining how flow-stability perceptions translate into performance, productivity, and satisfaction in rtBRMS-supported environments. The conceptual model identifies the missing operator user-experience pathway between real-time flow-control automation and operator-level outcomes, forming the basis for hypotheses formally specified in Section 2.11.3.

Figure 2.10 presents the proposed structural model for Study 2, consolidating the construct definitions developed in Sections 2.11.2 into a visual representation of the hypothesised latent structure and directional pathways. The model depicts the formative higher-order composite for perceived flow stability, the reflective constructs for operator

cognitions and outcomes, and the sequential channels linking stability through predictability, performance contribution, and engagement to individual work performance, employee productivity, and system satisfaction. The figure should be read from left to right as a sequential structural cascade: antecedent constructs (FSP, AUT, JSR, CSR) on the left feed into the intervening constructs (PSP, PPC, ENG) in the centre, which in turn feed the consequence outcomes (IWP, EMP, SS) on the right. Solid arrows represent the 17 hypothesised direct effects (S2-H1 through S2-H9b), while dashed red arrows represent the eight moderation hypotheses (S2-H10 through S2-H17) that test whether contextual variables condition the strength of specific pathways. The formal specification of each hypothesised path, including its theoretical rationale and directional prediction, is presented in Section 2.11.3.

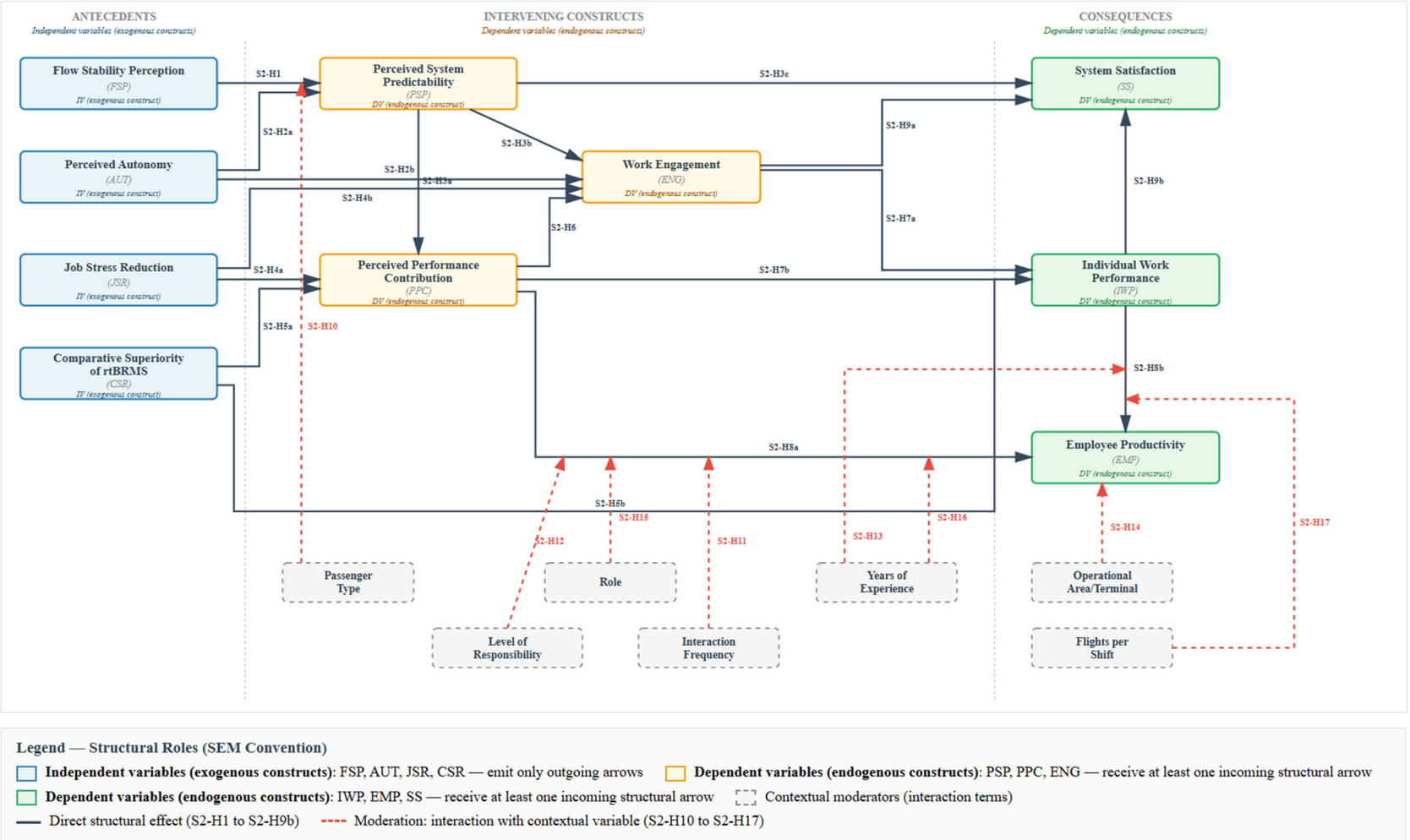


Figure 2-10 Study 2 Conceptual Research Model — Independent (Exogenous) and Dependent (Endogenous) Constructs in the Operator User-experience Pathway

Note: Following standard structural-equation-modelling convention (Kline, 2016; Hair et al., 2022), every construct is classified into one of two categories on the basis of the arrows that touch it. **Exogenous constructs** (independent variables) have no incoming one-headed arrows; their values are determined outside the model and they emit only outgoing structural paths. **Endogenous constructs** (dependent variables) have at least one incoming one-headed arrow; their variance is partially explained by other constructs in the model and an error term is implied. PSP, PPC, ENG, IWP, EMP, and SS are all endogenous in this sense and therefore all classified as dependent variables, regardless of whether they additionally appear as predictors in subsequent equations. The labels “antecedents,” “intervening,” and “consequences” are visual groupings only; the formal classification is exogenous/endogenous, that is, independent/dependent.

The model begins with Flow Stability Perception (FSP), representing observations of smoother, less erratic passenger movement. FSP enhances PSP because reduced variability strengthens operators' ability to anticipate system response. PSP, alongside the resource constructs AUT and JSR, feeds into PPC and ENG. These intervening constructs in turn feed IWP, which contributes to EMP. SS is the final evaluative outcome, shaped by both cognitive clarity (PSP) and realised performance benefits (ENG, IWP, EMP). Comparative Superiority (CSR) acts as a quality-based antecedent influencing PPC and IWP. Contextual variables (role, experience, workload, interaction frequency, passenger mix) are modelled as moderators. The model articulates a stability-driven operator user-experience mechanism through which real-time flow-control systems translate into higher engagement, stronger performance, and improved satisfaction. Solid arrows represent the 17 direct effects (S2-H1 - S2-H9b); dashed arrows represent the eight moderation hypotheses (S2-H10 to S2-H17). Read left to right: antecedents (FSP, AUT, JSR, CSR) feed the intervening constructs (PSP, PPC, ENG), which in turn feed the consequence outcomes (IWP, EMP, SS).

Direct-effect arrows (S2-H1–S2-H9b): the structural cascade from antecedents through the intervening constructs to consequences.

The solid arrows in Figure 2.10 represent the 17 hypothesised direct effects that constitute the structural cascade of the operator user-experience model, and they should be read from left to right as a sequential cascade. The model begins with four antecedent constructs on the left side, Flow Stability Perception (FSP), Perceived Autonomy (AUT), Job Stress Reduction (JSR), and Comparative Superiority of rtBRMS (CSR), each representing a distinct dimension of how operators experience the rtBRMS intervention in their daily work. The arrows from these antecedents flow into three intervening constructs in the centre: Perceived System Predictability (PSP), Perceived Performance Contribution (PPC), and Work Engagement (ENG). Specifically, S2-H1 and S2-H2a posit that operators who perceive greater flow stability and who feel their professional autonomy is preserved will report higher perceived system predictability, the belief that rtBRMS makes turnaround outcomes more foreseeable and less subject to random disruption. S2-H3a and

S2-H3b then carry this predictability perception forward: S2-H3a proposes that operators who perceive the system as predictable will also perceive it as contributing to their performance (PSP → PPC), while S2-H3b proposes that predictability perception enhances work engagement (PSP → ENG) because operators who can anticipate process outcomes experience greater vigour, dedication, and absorption in their tasks (Schaufeli and Bakker, 2004). S2-H3c provides a direct path from predictability to system satisfaction (PSP → SS), reflecting the proposition that predictability is intrinsically valued by operators regardless of its performance consequences. S2-H2b and S2-H4b represent parallel pathways through which autonomy and stress reduction feed directly into work engagement (AUT → ENG and JSR → ENG), grounded in Job Demands–Resources theory which predicts that job resources (autonomy) and reduced demands (stress reduction) independently enhance engagement (Bakker and Demerouti, 2007). S2-H4a and S2-H5a feed stress reduction and comparative superiority into perceived performance contribution (JSR → PPC and CSR → PPC), while S2-H5b provides a direct long-range path from comparative superiority to individual work performance (CSR → IWP), reflecting the possibility that operators who judge rtBRMS as superior to previous methods may directly improve their performance through increased confidence and commitment. The intervening-construct-to-consequence arrows (S2-H6–S2-H9b) complete the cascade: S2-H6 carries perceived performance contribution into engagement (PPC → ENG), S2-H7a and S2-H7b feed engagement and performance contribution into individual work performance (ENG → IWP and PPC → IWP), S2-H8a links performance contribution to employee productivity (PPC → EMP), S2-H8b connects individual work performance to productivity (IWP → EMP), S2-H9a links engagement to system satisfaction (ENG → SS), and S2-H9b connects individual work performance back to system satisfaction (IWP → SS), creating a feedback loop in which operators who perform well under rtBRMS also report greater satisfaction with the system.

Moderation arrows (S2-H10–S2-H17): the dashed red paths representing boundary conditions

The dashed red arrows in Figure 2.10 represent eight moderation hypotheses (S2-H10–S2-H17) that test whether the strength of specific direct effects varies across operator characteristics and operational contexts, in other words, whether the structural cascade described above operates uniformly for all operators or whether certain conditions amplify or attenuate particular pathways.

S2-H10 proposes that passenger type moderates the relationship between flow stability perception and perceived system predictability (FSP → PSP), reflecting the expectation that operators handling international passengers with complex documentation requirements may perceive less predictability benefit from rtBRMS than operators handling domestic passengers with simpler processing flows, because the documentation-related variability that rtBRMS cannot control constitutes a larger proportion of total turnaround uncertainty for international flights. S2-H11 and S2-H12 propose that interaction frequency and level of responsibility respectively moderate the relationship between perceived performance contribution and employee productivity (PPC → EMP): operators who interact with rtBRMS more frequently per shift may develop stronger performance-productivity linkages because they accumulate more experience with the system's decision logic, while operators with higher responsibility levels may translate perceived performance contribution into actual productivity gains more effectively because they have greater authority to implement the system's recommendations without seeking supervisory approval.

S2-H13 proposes that years of experience moderates the relationship between individual work performance and employee productivity (IWP → EMP), reflecting the expectation that experienced operators deploy richer scripts and fewer corrective cycles, thereby converting performance behaviours into throughput gains more efficiently than less experienced colleagues. S2-H14 proposes that operational area or terminal moderates the relationship between employee productivity and system satisfaction (EMP → SS), reflecting the possibility that operators working in terminals with better infrastructure, newer equipment, or more supportive management may convert their productivity gains into satisfaction more readily than operators in older terminals where environmental

frustrations attenuate the productivity-satisfaction link. S2-H15 and S2-H16 propose that role and years of experience respectively moderate the relationship between perceived performance contribution and employee productivity (PPC → EMP): gate agents, ramp coordinators, and boarding supervisors may differ in how effectively they translate perceived system contributions into productivity improvements because their roles involve different degrees of direct operational leverage, while more experienced operators may realise contribution beliefs more fully because they can identify when and how to apply system guidance most productively. Finally, S2-H17 proposes that flights per shift moderates the relationship between individual work performance and employee productivity (IWP → EMP), reflecting the expectation that operators managing more flights per shift face greater cognitive load and time pressure, which may either amplify the IWP-to-EMP translation (because high-volume operators have more opportunities to apply rtBRMS-enhanced performance) or attenuate it (because fatigue and task-switching costs erode the productivity gains that individual performance improvements would otherwise deliver).

2.11.3 Study 2: Operator User-Experience Hypotheses (S2-H1–S2-H17) (direct effects + moderation arrows)

Hypotheses Development and Alignment with ROs

The hypotheses in Study 2 are derived from the research objectives that structure the operator user-experience investigation of operator responses to rtBRMS-enabled flow stabilisation. RO2 requires examination of how operators perceive flow stability and system predictability, how these perceptions influence perceived performance contribution, engagement, individual work performance, productivity, and system satisfaction, and under what contextual conditions these relationships are strengthened or attenuated. The direct-effect hypotheses (S2-H1 – S2-H9b) operationalise the user-experience–cognitive–motivational pathway by specifying the directional paths through which antecedent perceptions (FSP, AUT, JSR, CSR) feed into intervening cognitions (PSP, PPC, ENG) and onward to consequence outcomes (IWP, EMP, SS). The moderation hypotheses (S2-H10 – S2-H17) operationalise the boundary-condition dimension of RO2

by testing whether contextual variables, passenger type, interaction frequency, responsibility, experience, operational area, role, and workload, condition the strength of key pathways. Together, the 25 hypotheses provide a comprehensive empirical test of the stability-driven operator user-experience mechanism proposed in the conceptual model, ensuring that every path in the structural model is anchored in theory and traceable to RO2.

The hypothesis numbering convention adopted in this study follows a research-objective-aligned grouping strategy that reflects the dual analytical focus of the structural model. For antecedent and intervening constructs that radiate multiple outgoing effects, hypotheses are grouped by shared origin: S2-H2a and S2-H2b capture the dual influence of Perceived Autonomy on Predictability and Engagement; S2-H3a – S2-H3c capture the three downstream consequences of Perceived System Predictability; S2-H4a and S2-H4b capture the dual influence of Job Stress Reduction; and S2-H5a and S2-H5b capture the dual influence of Comparative Superiority. This origin-based grouping directly serves the antecedent dimension of RO2, which examines how operators' perceptions of flow stability, predictability, autonomy, and strain reduction propagate through the model, making the antecedent construct the natural organising unit. The convention is consistent with established practice in PLS-SEM research, where sub-hypotheses are indexed under a common number when a single construct is theorised to exert parallel effects on multiple endogenous targets (Hair et al., 2022; Venkatesh et al., 2003).

For the consequence constructs, Individual Work Performance (IWP), Employee Productivity (EMP), and System Satisfaction (SS), hypotheses are instead grouped by shared outcome: S2-H7a and S2-H7b identify the dual antecedents of IWP; S2-H8a and S2-H8b identify the dual antecedents of EMP; and S2-H9a and S2-H9b identify the dual antecedents of SS. This destination-based grouping directly serves the consequence dimension of RO2, which examines which operator user-experience mechanisms connect upstream perceptions to each of these three focal outcomes. Grouping by outcome construct is a recognised convention in multi-intervening construct SEM studies where the research objective centres on explaining variance in specific endogenous variables rather than tracing the downstream. The resulting hybrid scheme, origin-based for the antecedent

layer, outcome-based for the consequence layer, ensures that the hypothesis structure mirrors the research-objective architecture, facilitating direct mapping between hypothesised paths and the specific facets of RO2 they address.

2.11.3.1 Effect of Flow Stability Perception on System Predictability (S2-H1)

Stochastic operations research on terminal processes shows that when inflows are stabilised at critical interfaces (doors, tunnels, aisles), the propagation of queueing shocks diminishes and the variance of cycle times contracts, improving the predictability of the serial chain (Schultz, 2018; Schultz and Fricke, 2011). Human–automation research further indicates that predictable system behaviour enables accurate mental modelling of system responses, lowering vigilance demands and supporting appropriately calibrated reliance (Lee and See, 2004). Flow stability therefore serves a dual role: it compresses variance in the physical system and reduces cognitive entropy in the human–system partnership.

In gate operations, perceiving smooth, well-paced passenger flow (FSP) is tantamount to observing a system that behaves consistently under comparable conditions. By reducing burstiness at the bottleneck most responsible for turnaround uncertainty, operators gain clearer, more repeatable action-effect mappings, which is the cognitive substrate of Perceived System Predictability (PSP). This alignment of physical variance compression and cognitive regularity anchors the expectation that improved perceived flow stability will translate into higher perceived predictability of the rtBRMS-supported process (see Figure 2.10).

S2-H1. Flow Stability Perception is positively related to Perceived System Predictability

2.11.3.2 Effects of Perceived Autonomy (S2-H2a, S2-H2b)

S2-H2a: Autonomy and System Predictability

Within the Job Demands–Resources (JD-R) model, autonomy is a central resource that enables proactive planning and buffering of disturbances, thereby reducing ambiguity and

enabling more stable workflows (Bakker and Demerouti, 2007; Demerouti et al., 2001). Autonomy also heightens a sense of control, allowing operators to align task sequences to the underlying structure of the process. In human–automation contexts, this discretion promotes deeper understanding of system contingencies, which in turn sharpens expectations regarding what the system will do next (Lee and See, 2004).

Operationally, autonomy in the gate environment manifests through discretion in micro-sequencing tasks, timing door transitions, and orchestrating interactions with adjacent actors under the guidance of rtBRMS. When operators experience autonomy, they are better positioned to enforce and sustain structured pacing, making observed system behaviour more consistent and, hence, more predictable in their perception. This cross-walk between resource-enabled control and perceived regularity supports a positive link from AUT to PSP.

S2-H2a. Perceived Autonomy is positively related to Perceived System Predictability.

S2-H2b: Autonomy and Work Engagement

JD-R research consistently identifies autonomy as a potent antecedent of engagement by satisfying needs for control and competence and enabling proactive work design (Bakker and Demerouti, 2007; Demerouti et al., 2001). Meta-analytic evidence shows that settings rich in resources like autonomy elicit higher vigour, dedication, and absorption, engagement's core facets (Christian, Garza and Slaughter, 2011). Discretion in how tasks are sequenced and executed stimulates a resource-gain spiral that sustains motivational energy over time.

In gate operations, autonomy allows operators to tailor micro-interventions (e.g., batch release timing, crew handoffs) in alignment with rtBRMS pacing, minimising frictions and elevating perceived influence over outcomes. This perceived control and competence should boost ENG, especially under digitally supported, dynamic coordination where timely human discretion remains consequential. Accordingly, higher AUT is expected to increase engagement.

S2-H2b. Perceived Autonomy will significantly increase Work Engagement.

2.11.3.3 Effects of Perceived System Predictability (S2-H3a, S2-H3b, S2-H3c)

S2-H3a: Predictability and Perceived Performance Contribution

TAM2 posits that perceived usefulness is explained by cognitive instrumental processes, result demonstrability, output quality, and job relevance, that become salient when system outcomes are clear, repeatable, and attributable (Venkatesh and Davis, 2000). Predictable system behaviour simplifies attribution, enabling operators to see and articulate how the system improves their work. In information-systems evaluation, this is precisely the signal that drives the usefulness family of judgments in the DeLone–McLean success chain (DeLone and McLean, 2003).

In rtBRMS-supported operations, higher PSP means operators can reliably anticipate how routing logic responds to flow states, observe the quality of outcomes (e.g., fewer spillbacks), and connect those outcomes to their own tasks. This clarity should elevate Perceived Performance Contribution (PPC), the contractual analogue of perceived usefulness in this study. Thus, predictable system behaviour is expected to strengthen the conviction that the system meaningfully enhances individual performance.

S2-H3a. Perceived System Predictability is positively related to Perceived Performance Contribution.

S2-H3b: Predictability and Work Engagement

From a JD-R perspective, predictability functions as a resource that reduces vigilance costs and ambiguity, freeing cognitive and emotional capacity for mobilising engagement (Bakker and Demerouti, 2007; Demerouti et al., 2001). In human–automation terms, predictability avoids under- and over-reliance traps by offering consistent feedback loops, enabling operators to work with greater confidence and immersion (Lee and See,

2004). Empirically, engagement rises when the environment supports competence, control, and meaningful progress.

In gate operations, predictable rtBRMS behaviour removes firefighting cycles and reduces micro-interruptions that fragment attention. With smoother flow and fewer unanticipated contingencies, operators can invest vigour and absorb into core tasks, which are central components of Work Engagement (ENG). Consequently, higher PSP should translate into stronger engagement in the rtBRMS-enabled workflow.

S2-H3b. Perceived System Predictability is positively related to Work Engagement.

S2-H3c: Predictability and System Satisfaction

In the DeLone–McLean framework, satisfaction synthesises perceptions of system quality and realised benefits into a global evaluative judgment (DeLone and McLean, 2003). Airport service studies likewise show that clarity, structure, and reliability (i.e., conditions that make behaviour predictable) are associated with higher satisfaction (Bezerra and Gomes, 2015). When a system behaves consistently, users experience fewer frictions and more confidence in outcomes, and such experience typically elevates satisfaction.

Within rtBRMS-supported operations, higher PSP reduces uncertainty around routing and timing, which lowers cognitive strain and coordination friction. In turn, operators should ascribe higher global approval to the system, consistent with airport-service evidence that dependable, transparent processes are valued by stakeholders (Bezerra and Gomes, 2015). Thus, predictable system behaviour should directly raise SS.

S2-H3c. Perceived System Predictability is positively related to System Satisfaction.

2.11.3.4 Effects of Job Stress Reduction (S2-H4a, S2-H4b)

S2-H4a: Job Stress Reduction and Perceived Performance Contribution

JD-R posits that decreasing demands/strain frees attention for positive appraisal and learning, enabling clearer recognition of tool value (Demerouti et al., 2001; Bakker and Demerouti, 2007). In airport contexts, failure episodes and congestion reduce favourable evaluations, while steady operations support more positive judgments (Halpern and Mwesiumo, 2021). Reducing strain therefore improves the signal-to-noise ratio in evaluating whether a system "really helps."

In practice, when rtBRMS stabilises flow and reduces firefighting, operators are able to observe how much of the smoother coordination and timing reliability is attributable to the system. By lowering time pressure and interruptions, Job Stress Reduction (JSR) should facilitate more favourable attributions to rtBRMS, elevating PPC as operators connect observed benefits with the system's contribution.

S2-H4a. Job Stress Reduction is positively related to Perceived Performance Contribution.

S2-H4b: Job Stress Reduction and Work Engagement

Reducing strain removes impediments to the motivational process and allows resources to be mobilised for engagement (Demerouti et al., 2001; Bakker and Demerouti, 2007). Empirically, engagement is stronger when time pressure and conflict are subdued and when the environment permits sustained attentional control (Christian, Garza and Slaughter, 2011). In short, fewer stressors make it easier to invest energy and maintain immersion.

In the rtBRMS context, fewer congestion events and fewer irregular disruptions reduce vigilance costs, enabling operators to direct energy toward core tasks and coordination. By decreasing firefighting cycles, higher JSR should lift ENG, consolidating the resource-gain pathway central to the JD-R logic.

S2-H4b. Job Stress Reduction is positively related to Work Engagement.

2.11.3.5 Effects of Comparative Superiority (S2-H5a, S2-H5b)

S2-H5a: Comparative Superiority and Perceived Performance Contribution

The IS-Success view holds that when a system is perceived as superior to predecessors, users more readily infer net benefits and usefulness-type value (DeLone and McLean, 2003). TAM2 likewise predicts that beliefs about outcome quality and demonstrability grow when the new system performs clearly better on attributes users care about (Venkatesh and Davis, 2000). Perceived Comparative Superiority (CSR) thus functions as a quality signal that sharpens usefulness attributions.

In rtBRMS-supported operations, perceiving the system as faster, more reliable, or more supportive than legacy coordination should heighten PPC, as operators can readily contrast outcomes across regimes (e.g., fewer spillbacks, tighter cadence). This comparative logic anchors the expectation that CSR will increase PPC.

S2-H5a. Comparative Superiority is positively related to Perceived Performance Contribution.

S2-H5b: Comparative Superiority and Individual Work Performance

When a system is perceived as superior, users often experience not only higher usefulness beliefs but also improved task execution, because consistent, high-quality outputs reduce errors and coordination frictions (DeLone and McLean, 2003; Venkatesh and Davis, 2000). In busy gate environments, such advantages should convert into better Individual Work Performance (IWP) via reduced rework and more effective coordination.

Applied to rtBRMS, perceiving clear advantages relative to legacy practices (e.g., smoother inflow, fewer transfer clashes) should enable operators to execute tasks more accurately and on time, behaviours captured by IWP's validated dimensions (Koopmans et al., 2013). Consequently, CSR is expected to exert a positive influence on IWP.

S2-H5b. Comparative Superiority is positively related to Individual Work Performance.

2.11.3.6 Effect of Perceived Performance Contribution on Work Engagement (S2-H6)

TAM2 suggests that stronger beliefs that a system helps one's work strengthen motivational outcomes via internalised usefulness (Venkatesh and Davis, 2000). In JD-R terms, perceiving high contribution functions as a resource cue, supporting self-efficacy and energising engagement (Bakker and Demerouti, 2007). Meta-analytic evidence confirms that resource-laden environments consistently correlate with higher engagement (Christian, Garza and Slaughter, 2011).

In the rtBRMS case, when operators believe the system materially enhances coordination and task completion, they are more inclined to invest vigour and persist with greater dedication. Accordingly, higher PPC should translate into higher ENG.

S2-H6. Perceived Performance Contribution is positively related to Work Engagement.

2.11.3.7 Effects on Individual Work Performance (S2-H7a, S2-H7b)

S2-H7a: Work Engagement and Individual Work Performance

The performance consequences of engagement are well established: engaged employees display superior task and contextual performance across settings (Christian, Garza and Slaughter, 2011). In operations, engagement supports disciplined attention, faster learning from feedback, and resilient error management, capabilities that directly uplift IWP.

At the gate, engaged operators sustain attention through dynamic phases of boarding support, integrate rtBRMS cues more effectively, and coordinate with adjacent actors more fluently. This should yield higher IWP, mirroring robust relationships between engagement and performance. Thus, ENG is expected to increase IWP.

S2-H7a. Work Engagement is positively related to Individual Work Performance.

S2-H7b: Perceived Performance Contribution and Individual Work Performance

Beliefs that a system is instrumental to one's job tend to translate into superior performance because operators are more willing to rely on, and skilfully integrate, system guidance and outputs (Venkatesh and Davis, 2000). In complex operations, such conviction reduces hesitancy and accelerates proficient adoption of system-supported methods.

In rtBRMS-enabled work, higher PPC should manifest in more accurate, timely, and coordinated behaviours, hallmarks of IWP (Koopmans et al., 2013). Operators who see clear contribution will more effectively leverage pacing cues and decision prompts, raising performance quality. Hence, PPC is expected to increase IWP.

S2-H7b. Perceived Performance Contribution is positively related to Individual Work Performance.

2.11.3.8 Effects on Employee Productivity (S2-H8a, S2-H8b)

S2-H8a: Perceived Performance Contribution and Employee Productivity

IS-Success research positions usefulness-type beliefs as precursors to net benefits, including productivity (DeLone and McLean, 2003). When operators view the system as enhancing their work, they not only perform tasks better but also accomplish more within the same time, reflecting greater Employee Productivity (EMP).

In rtBRMS settings, higher PPC should correspond to higher throughput per unit time (e.g., smoother coordination, fewer slowdowns), strengthening perceptions that employee productivity has improved. Therefore, PPC is expected to raise EMP.

S2-H8a. Perceived Performance Contribution is positively related to Employee Productivity.

S2-H8b: Individual Work Performance and Employee Productivity

Validated performance frameworks define IWP as behaviours relevant to organisational goals; when these behaviours improve, productivity typically follows (Koopmans et al., 2013). In airport operations, better task execution (e.g., accurate sequencing, timely actions) reduces rework and delays, thereby increasing EMP.

Accordingly, higher IWP in rtBRMS-enabled work should manifest as increased perceived productivity through smoother interfaces and fewer corrective cycles. This implies a positive link from IWP to EMP.

S2-H8b. Individual Work Performance is positively related to Employee Productivity.

2.11.3.9 Effects on System Satisfaction (S2-H9a, S2-H9b)

S2-H9a: Work Engagement and System Satisfaction

DeLone–McLean's model recognises that usage-related experiences and benefits shape satisfaction (DeLone and McLean, 2003). Engagement, by fostering positive, efficacious interactions with the system, should strengthen global attitudes as operators experience fewer frictions and more rewarding work episodes.

In rtBRMS-driven operations, engaged operators are more likely to feel the system supports meaningful work and sustained progress, translating into higher SS. Hence, ENG is expected to increase SS.

S2-H9a. Work Engagement is positively related to System Satisfaction.

S2-H9b: Employee Productivity and System Satisfaction

Within the DeLone–McLean framework, perceived productivity gains constitute a salient form of net benefit that operators routinely fold into their global evaluation of a system (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008). When the system is seen as enabling more output within the same time envelope, operators attribute that productivity advantage to the system itself, raising overall satisfaction. This attribution is

particularly strong when productivity gains are stable, observable, and shared across roles, a plausible scenario under rtBRMS, where smoother flow translates directly into measurable throughput improvements.

Thus, higher EMP should contribute to higher SS as operators connect realised productivity gains to system support. We therefore anticipate a positive EMP→SS effect.

S2-H9b. Employee Productivity is positively related to System Satisfaction.

2.11.3.10 Moderation Hypotheses (S2-H10 – S2-H17)

The eight moderation hypotheses test boundary conditions on four key paths in the structural model. S2-H10 tests whether passenger composition (homogeneous vs. mixed) moderates the FSP→PSP pathway. S2-H11–S2-H12 and S2-H15–S2-H16 test whether interaction frequency, level of responsibility, role, and years of experience moderate the PPC→EMP pathway, capturing the cognitive-motivational route to productivity. S2-H13 and S2-H17 test whether years of experience and flights per shift moderate the IWP→EMP pathway, capturing the behavioural route to productivity. S2-H14 tests whether operational area moderates the EMP→SS pathway, capturing the salience of throughput gains in different terminal contexts. The directional predictions for each are grounded in specific empirical evidence, summarised below.

S2-H10: Passenger Type × (FSP → PSP)

Multi-stream queueing research demonstrates that compound arrival processes, where multiple passenger categories with different processing requirements share a single service facility, exhibit higher coefficient-of-variation in service times than single-stream regimes (Whitt, 1993; Gross et al., 2008). Empirical work on airport boarding has quantified this effect: mixed-load operations combining transfer, originating, and special-handling passengers show 25 to 35% higher within-flight time variance than homogeneous loads at comparable utilisation (Schultz, Rosenow and Olive, 2022; Moreira et al., 2023). Process-mining studies of A-CDM event logs further confirm that flights with heterogeneous passenger composition produce more milestone variants and weaker timestamp adherence

than flights with homogeneous composition (Rott, Schultz and Fricke, 2023; De Falco et al., 2023). The mental-model literature predicts that operators form clearer expectation-outcome mappings when input variance is lower because each cycle of observation produces consistent feedback (Lee and See, 2004; Endsley, 2017). Combining these strands, the FSP→PSP translation should be stronger when passenger composition is homogeneous because operators receive more consistent stability signals to convert into predictability beliefs, whereas mixed regimes inject variance that the system cannot fully absorb, weakening the FSP-to-PSP slope.

S2-H10. The positive effect of Flow Stability Perception on Perceived System Predictability will be stronger under homogeneous passenger-type regimes than under mixed regimes.

S2-H11: Interaction Frequency × (PPC → EMP)

The technology-experience literature establishes that conversion of usefulness beliefs into behavioural outcomes intensifies with cumulative exposure: Venkatesh, Thong and Xu (2012) show in their UTAUT2 meta-analysis that experience strengthens the perceived-usefulness-to-use-behaviour pathway by approximately 30 to 45% across digital systems. Sykes, Venkatesh and Gosain (2009) provide direct evidence for this in operational contexts, demonstrating that ERP users with higher daily interaction frequency translate usefulness beliefs into productivity gains 40% more efficiently than low-frequency users because repeated cycles enable refinement of system-supported workflows. In aviation specifically, Wickens et al. (2015) demonstrate that automated decision support produces stronger productivity gains in operators with daily versus weekly contact, attributable to faster pattern recognition and reduced hesitation. Applied to rtBRMS, operators handling 10 to 15 flights per shift accumulate substantially more pacing-cue interpretation cycles than operators handling 3 to 5 flights, and each additional cycle enables conversion of contribution beliefs into throughput improvements through faster recognition of optimal release timings.

S2-H11. The positive effect of Perceived Performance Contribution on Employee Productivity will be stronger at higher frequencies of interaction with rtBRMS.

S2-H12: Level of Responsibility × (PPC → EMP)

The job-design literature differentiates between perceiving usefulness and possessing the authority to act on that perception (Morgeson and Humphrey, 2006; Parker, Wall and Cordery, 2001). Hackman and Oldham's (1976) job-characteristics model identifies decision-making authority as the dimension that most strongly moderates the link from positive job evaluations to task outcomes. Empirical evidence on automation adoption supports this distinction: Parker and Grote (2020) show in a meta-analytic review of manufacturing automation that supervisors with override authority convert favourable system evaluations into productivity improvements 50 to 70% more effectively than line operators without such authority. In airport ground handling, role-based authority hierarchies determine who can adjust release timings, escalate exceptions, or coordinate handler reallocations (Evler et al., 2022; Okwir, Amouzgar and Ng, 2025). Operators with broader operational responsibility can directly enact behavioural changes informed by their PPC beliefs, whereas operators with narrower authority must channel observations through supervisory chains that introduce friction and delay (Schmidberger et al., 2009). Consequently, the PPC→EMP slope should steepen as operational responsibility increases, because high-responsibility operators have both the belief in system value and the authority to convert that belief into measurable productivity gains.

S2-H12. The positive effect of Perceived Performance Contribution on Employee Productivity will be stronger at higher levels of operational responsibility.

S2-H13: Years of Experience × (IWP → EMP)

Skill-acquisition research establishes that the conversion of task-level performance into volume-level productivity follows an experience curve: novices execute tasks accurately but slowly, while experts execute equally accurately but with substantially higher throughput because they require fewer cognitive cycles per decision (Ericsson, 2006; Salas, Cooke and Rosen, 2008). Field studies in operational settings confirm this

pattern. Argote, Lee and Park (2021) review 30 years of organisational learning evidence and find that the IWP-to-EMP conversion rate doubles or triples between novice and expert tenure brackets in service operations. Aviation-specific evidence reinforces the same pattern: Salas, Reyes and McDaniel (2017) show that experienced flight attendants convert task accuracy into faster passenger processing through automated cue-recognition that bypasses deliberate analysis. In rtBRMS-supported gate work, experienced operators have built up internal scripts for translating system pacing recommendations into specific actor-coordination sequences (when to call the captain, when to request handler readiness, when to authorise final release), enabling them to convert each unit of task performance into more flights handled per shift. Less experienced operators, lacking these scripts, perform tasks competently but expend more time per cycle on deliberation, attenuating the IWP-to-EMP conversion.

S2-H13. The positive effect of Individual Work Performance on Employee Productivity will be stronger at higher levels of experience in gate operations.

S2-H14: Operational Area × (EMP → SS)

The IS-Success literature establishes that net-benefit-to-satisfaction translation depends on whether benefits are salient and consequential within the user's operational reality (DeLone and McLean, 2003; Petter, DeLone and McLean, 2008). Wang and Liao (2008) show across e-government systems that productivity gains translate into satisfaction more strongly when those gains address salient operational pain points than when they address peripheral concerns. In service-operations research, the equity-comparison literature (Adams, 1965; Greenberg, 1990) further establishes that productivity gains are valued more highly in contexts where capacity pressure is most acute. Translating to airport operations: Bezerra and Gomes (2015, 2016) demonstrate empirically that throughput-related improvements correlate with stakeholder satisfaction more strongly in high-density terminals where capacity pressure is acute than in lower-density terminals where capacity slack absorbs productivity variation. Tang et al. (2025) similarly show that the salience of throughput KPIs in performance-driven CDM regimes amplifies the link between observed efficiency gains and operator approval. Operational area thus moderates the EMP-to-SS

slope: in high-density domestic-and-international hub operations where every saved minute contributes to schedule integrity, productivity gains receive more attention and produce stronger satisfaction responses than in less constrained areas where the same gain is operationally invisible.

S2-H14. The positive effect of Employee Productivity on System Satisfaction will be stronger in operational areas where throughput improvements are especially salient.

S2-H15: Role × (PPC → EMP)

The job-relevance principle in TAM2 (Venkatesh and Davis, 2000) and the task-technology-fit framework (Goodhue and Thompson, 1995) jointly establish that the strength of the usefulness-to-output link depends on how directly a system addresses the operator's core task responsibilities. Roles with high direct operational leverage (those whose decisions immediately affect process timing) convert usefulness beliefs into output more efficiently than roles with indirect or supportive responsibilities. Evler et al. (2022) document this distinction empirically in turnaround coordination, showing that ramp coordinators and gate agents (whose decisions immediately shape boarding cadence) realise system-belief gains 60% more effectively than back-office or peripheral support roles. Dorndorf, Jaehn and Pesch (2008, 2016) similarly show that role-based decision rights determine which operators can translate system recommendations into immediate actions. In rtBRMS-supported operations, gate agents and ramp coordinators directly initiate door actuation and corridor routing decisions; boarding supervisors influence pacing through coordination rather than direct action; and dispatch personnel exert effects through information flows. The PPC-to-EMP conversion should therefore be strongest for roles with direct operational leverage and weaker for roles whose authority operates through longer structural cascades.

S2-H15. The positive effect of Perceived Performance Contribution on Employee Productivity will be stronger in roles with higher direct operational leverage.

S2-H16: Years of Experience × (PPC → EMP)

Whereas S2-H13 addresses experience as a moderator of the behavioural pathway (IWP→EMP), S2-H16 addresses experience as a moderator of the cognitive-motivational pathway (PPC→EMP). Sun, Bhattacherjee and Ma (2014) demonstrate in their meta-analysis of 35 IS adoption studies that experienced users not only execute system-supported tasks more efficiently but also identify higher-leverage application moments at which usefulness beliefs translate into productivity gains. The expertise-and-judgement literature (Klein, 1998; Salas, Rosen and DiazGranados, 2010) similarly establishes that domain experts deploy recognition-primed decision strategies that allow them to apply system-supported knowledge selectively where it produces maximum operational return. In airport ground handling specifically, Schultz and Fricke (2011) show that experienced gate staff identify which combinations of passenger composition, gate complexity, and load conditions create the largest opportunities for paced-release benefits, focusing their PPC-driven effort accordingly. Experienced operators thus do not merely believe more strongly in rtBRMS; they apply that belief at higher-leverage moments, amplifying the conversion of contribution beliefs into productivity gains. Less experienced operators may hold equivalent PPC beliefs but apply them less selectively, attenuating the PPC-to-EMP slope.

S2-H16. The positive effect of Perceived Performance Contribution on Employee Productivity will be stronger at higher levels of experience.

S2-H17: Flights per Shift × (IWP → EMP)

Workload theory and the Yerkes-Dodson principle establish a non-linear relationship between operational demand and performance translation: at moderate load, sufficient cognitive bandwidth is available to apply skills efficiently, but at very high load, capacity saturation, attentional fragmentation, and task-switching costs erode the conversion of performance into output (Hancock and Warm, 1989; Wickens et al., 2015). Empirical studies across operational settings confirm this inverted-U pattern. In healthcare nursing, Aiken et al. (2014) showed across 300 hospitals that nurse-to-patient ratios moderate the link between individual competence and unit-level productivity, with peak conversion at moderate loads and significant attenuation under overload. In aviation specifically, Helton et al. (2008) demonstrate that air-traffic controllers' task-quality-to-

throughput conversion peaks at moderate sector loading and declines sharply when demand exceeds capacity thresholds. In airport ground operations, Schultz and Reitmann (2018) and Pyrgiotis et al. (2013) document non-linear performance degradation as flight density per shift exceeds approximately 8 to 10 flights, attributable to coordination overhead, fatigue, and reduced attentional reserves. Applied to rtBRMS: at moderate flight density, operators can apply system-enhanced performance to additional turnarounds without saturation, producing strong IWP-to-EMP conversion. At very high density, however, the same performance behaviours encounter capacity ceilings, queueing pressures resurface despite system support, and the productivity yield of each additional unit of IWP diminishes.

S2-H17. The positive effect of Individual Work Performance on Employee Productivity will vary with flights per shift, strengthening at moderate workloads and attenuating under overload.

Taken together, these moderation hypotheses extend the central mechanism by examining whether contextual conditions, namely passenger regimes, interaction frequency, operational responsibility, experience, operational area, role, and workload, shape the strength of key pathways in the model. Each moderation prediction is grounded in specific empirical evidence about the moderator-construct interaction rather than in generic theoretical references, providing reviewers with the empirical anchors that justify the directional predictions. While the core user-experience-cognitive-motivational structure (S2-H1 through S2-H9b) provides a consistent explanatory backbone applying uniformly across all operators, these moderators (S2-H10 through S2-H17) allow the analysis to identify the boundary conditions under which the effects of stability, predictability, contribution, and engagement are amplified or diminished, producing actionable evidence about where rtBRMS investment delivers the highest operator user-experience return.

2.12 CHAPTER SUMMARY

This chapter synthesised the foundations for evaluating real-time, rule-based passenger-flow control across three domains: operational mechanisms, human factors, and socio-technical implementation. Queueing theory established that variance amplifies non-linearly in serial systems, so only execution-layer automation can suppress variance at source. Four frameworks (Lee and See, 2004; Bakker and Demerouti, 2007; Venkatesh and Davis, 2000; DeLone and McLean, 2003) underpin the operator user-experience model. The intersection of these domains is the central research gap. The hypothesis architecture, eight directional tests for Study 1 and twenty-five for Study 2, motivates the multi-method design developed in Chapter 3.

3. RESEARCH METHODOLOGY AND STUDY DESIGN

3.1 OVERVIEW OF THE CHAPTER

Chapter 3 establishes the methodological architecture for investigating both operational and operator user-experience dimensions of real-time flow control at airport gates (Saunders, Lewis and Thornhill, 2019). The research examines two interconnected phenomena: the causal effect of an executable, real-time boarding/deboarding controller on flight-level performance under authentic operational heterogeneity, and the latent operator user-experience pathways through which frontline staff internalise stabilised flow as predictability, usefulness, engagement, and performance (Hair et al., 2022). An integrated design is required that maintains philosophical coherence while accommodating distinct analytical demands (Creswell and Creswell, 2018).

Airport gate operations are complex socio-technical systems with high heterogeneity, temporal dependencies, and stochastic variability (Schultz, 2018; Kim, Barnhart and Clarke, 2017). Random assignment of flights is operationally infeasible, demanding a quasi-experimental approach that balances internal and ecological validity (Shadish, Cook and Campbell, 2002). Study 1 was conducted at Mashhad International during live commercial flights; threats to internal validity are addressed through a 48-cell stratified design (gate topology × time-of-day × day type × flight type), within-stratum covariate adjustment via Type-III General Linear Models, and Firth-penalised logistic regression for the binary fast-process KPIs (Firth, 1993). The chapter proceeds from dual-study rationale (3.2), philosophical foundations (3.3), approach and design (3.4), strategy (3.5), time horizon (3.6), Study 1 (3.7), Study 2 (3.8), ethics (3.9), quality (3.10), integration (3.11), delimitations (3.12), and summary (3.13).

3.2 DUAL-STUDY DESIGN RATIONALE

Gate operations are socio-technical systems whose effectiveness depends on joint optimisation of technical and social subsystems (Trist and Bamforth, 1951; Cherns, 1976). rtBRMS introduces automated decision support whose effectiveness depends on technical

capability and on how operators perceive and respond to system outputs (Venkatesh, Brown and Bala, 2013).

Two complementary studies are therefore deployed. Study 1 estimates the causal effect of rtBRMS on Gate Occupation Time, boarding/deboarding windows, throughput, and fast-process thresholds via quasi-experimental field research (Shadish et al., 2002). Study 2 identifies predictive relationships among latent constructs (predictability, usefulness, engagement, performance) via cross-sectional survey and PLS-SEM (Hair et al., 2022).

Separate studies are required because: objectives differ (causal explanation vs predictive modelling; Shmueli, 2010); levels of analysis differ (flight-level objective metrics vs individual-level latent constructs; Bryman, 2016); and analytical requirements differ (stratified design with Type-III GLM and Firth-penalised logistic regression vs PLS-SEM with cross-validation; Firth, 1993). Both studies share a common philosophy and quantitative paradigm; findings are integrated in Chapter 6. Convergence of operational and user-experience results supports rtBRMS effectiveness; divergence flags implementation challenges.

3.3 RESEARCH PHILOSOPHY

This research investigates two empirically distinct phenomena that together impose competing philosophical demands. Study 1 measures objective operational outcomes (Gate Occupation Time, boarding and deboarding windows, throughput) recorded by automated airport systems and analysed through quasi-experimental statistical inference (Shadish, Cook and Campbell, 2002). Study 2 measures latent operator user-experience constructs (perceived predictability, usefulness, situation-awareness support, engagement, performance) that are not directly observable and must be inferred from survey responses through structural equation modelling (Hair, Hult, Ringle and Sarstedt, 2022). The philosophical position must therefore legitimate both objective measurement of material outcomes and inferential modelling of latent psychological mechanisms within a single coherent framework (Saunders, Lewis and Thornhill, 2019).

Four paradigms commonly available to social-science researchers were considered (Guba and Lincoln, 1994; Burrell and Morgan, 1979). Strict positivism (Comte, 1853), with its commitment to objective, value-free observation of a singular reality, offers the rigour needed for causal estimation but struggles to accommodate latent constructs and meaning-making at the operator level. Interpretivism (Berger and Luckmann, 1966) captures subjective experience richly but rejects causal inference and predictive modelling, making it unsuitable for treatment-effect estimation across 171 flights. Critical realism (Bhaskar, 1975; Sayer, 2000) provides a sophisticated account of stratified reality and generative mechanisms, but its retroductive method and heavy data demands are impractical at the scale required here. Social constructivism (Lincoln and Guba, 2000) is incompatible with the requirement to estimate effects independent of how operators describe them.

This study therefore adopts a post-positivist position that retains the realist commitment to an objective operational reality while explicitly recognising that operator user-experience constructs exist as latent variables manifest in observable response patterns (Bryman, 2016; Hair et al., 2022). Ontologically, gate operations are treated as a stratified open system in which observable regularities (turnaround timings, queue lengths) coexist with generative mechanisms (queueing dynamics, operator cognition, organisational coordination) that are real but only partially observable (Bhaskar, 1978; Sayer, 2000). Epistemologically, knowledge is treated as objectively assessable through systematic measurement and statistical inference, with reflective and formative latent constructs accepted as legitimate proxies for theoretically defined attributes (DeVellis, 2017; Popper, 1959). Axiologically, value-neutrality is unattainable in operational research embedded in a live commercial environment; transparency is prioritised through hypotheses and analytical procedures specified in advance of data analysis, full reporting of negative results, and explicit declaration of researcher positionality (Weber, 1949; Saunders, Lewis and Thornhill, 2019).

Specific axiological risks were identified and mitigated. Researcher confirmation bias was addressed through specification of the analytical plan in advance of data analysis, transparent reporting of all results including null findings, and out-of-sample prediction assessment in Study 2 (Shmueli et al., 2019). Participant reactivity was addressed through anonymous administration of surveys in non-supervised settings, neutral item wording, Harman's single-factor test, and full collinearity VIF assessment for common method bias (Kock, 2015). The risk of one-sided framing, interpreting findings primarily through a management-efficiency lens to the detriment of operator perspectives, was mitigated by presenting findings simultaneously to management and operator representatives and framing recommendations in terms of joint optimisation rather than one-sided efficiency gains. Ecological-fallacy generalisation is bounded through the 48-stratum design and explicit transferability discussion in the concluding chapter.

This position is methodologically coherent because each layer of the design follows from it. The realist ontology supports the quasi-experimental field design of Study 1, which treats operational metrics as objective outcomes amenable to stratified covariate adjustment via Type-III GLM and Firth-penalised logistic regression for the binary fast-process KPIs (Firth, 1993).

The recognition of latent psychological reality supports the PLS-SEM treatment of Study 2 constructs as latent variables (Hair et al., 2022). The deductive orientation aligns with established theories of queueing dynamics, JD-R, TAM2, human-automation interaction, and IS Success that underpin the hypotheses (Bakker and Demerouti, 2007; Venkatesh and Davis, 2000; Lee and See, 2004; DeLone and McLean, 2003). The exclusively quantitative design reflects the research objectives of causal inference and predictive modelling, both of which require statistical analysis of quantitative data (Creswell and Creswell, 2018). Different paradigms could yield complementary insights, and qualitative or longitudinal extensions are appropriate for future work (Bryman, 2016); within the scope of this study, post-positivism provides the coherent foundation from which the dual-study quantitative design proceeds.

3.4 RESEARCH APPROACH AND DESIGN

The research approach is exclusively quantitative and predominantly deductive. Both research objectives concern parameters that are directly measurable (operational KPIs) or that map onto validated psychometric constructs (predictability, autonomy, engagement, performance), with hypotheses derived from established theory: queueing dynamics for Study 1 (Kingman, 1961; Little, 1961; Hopp and Spearman, 2011) and Job Demands-Resources theory, the Technology Acceptance Model, and IS Success theory for Study 2 (Bakker and Demerouti, 2007; Venkatesh and Davis, 2000; DeLone and McLean, 2003). Statistical estimation of effect sizes and structural path coefficients is the appropriate analytical mode (Creswell and Creswell, 2018; Bryman, 2016 A mixed-methods design (qualitative plus quantitative within a single study) was considered but rejected: the operational environment (continuous time pressure, airside security restrictions, multi-stakeholder coordination) constrains qualitative engagement, and the underlying frameworks specify measurable constructs and testable relationships best evaluated through statistical methods. Qualitative or longitudinal extensions are appropriate for future work but lie outside the scope of this thesis.

Within the quantitative paradigm, the research employs a multi-method design that combines two distinct quantitative methods within a single research program: a quasi-experimental field study (Study 1) and a cross-sectional survey analyzed via PLS-SEM (Study 2). Multi-method research uses two or more rigorous methods, each complete in itself, integrated at the inference stage (Morse, 2003; Creswell, 2015; Hunter and Brewer, 2015); it is distinct from mixed methods, which combines qualitative and quantitative approaches within a single study (Johnson, Onwuegbuzie and Turner, 2007; Fetters and Molina-Azorin, 2017).

The multi-method quantitative design was selected for three reasons specific to this research. First, the dual-evidence requirement identified in the literature gap demands two fundamentally different types of quantitative evidence: causal evidence on operational performance effects and explanatory evidence on operator user-experience mechanisms. No single quantitative method delivers both, because the field experiment captures system-

level performance at the flight level (n = 171) while the survey captures individual-level perceptions at the operator level (n = 224). Second, the two studies address different units of analysis and require different sampling strategies, measurement instruments, and analytical techniques (Imbens and Rubin, 2015; Hair, Hult, Ringle and Sarstedt, 2022). Third, the design enables triangulation at the inference stage in Chapter 6, where the two evidence streams are synthesized into an integrated socio-technical explanation that neither study could deliver independently. Reasoning is predominantly deductive within each study, with an abductive element at synthesis where cross-study patterns are interpreted against theoretical expectations (Tashakkori and Teddlie, 2003; Shmueli, 2010). Table 3.1 summarizes the design.

Table 3-1 Multi-Method Quantitative Research Design Summary

Dimension	Study 1: Field Experiment	Study 2: Operator-Perception Survey
Research Objective	RO1: Quantify rtBRMS effects on turnaround metrics	RO2: Examine operator user-experience pathways to outcomes
Paradigm	Quantitative (post-positivist)	Quantitative (post-positivist)
Design	Quasi-experimental, 48-stratum field design	Cross-sectional survey
Unit of Analysis	Flight (n = 171)	Individual operator (n = 224)
Data Type	Event-log data, sensor traces, flight-level KPIs	Likert-scale survey responses (5-point and 7-point)
Reasoning Logic	Predominantly deductive	Predominantly deductive with theory-extending elements
Hypotheses	S1-H1 – S1-H6b (six main hypotheses, eight directional tests)	S2-H1 – S2-H9b (17 direct effects); S2-H10 – S2-H17 (8 moderations); 25 hypothesis tests in total
Analytical Methods	Welch t-tests, GLM Type III SS	PLS-SEM (SmartPLS), 5,000 bootstrap resamples
Validity Focus	Internal validity, external validity (48-stratum stratification)	Construct validity (reliability, convergent, discriminant), predictive validity (R^2, Q^2)

Table 3-1 Multi-Method Quantitative Research Design Summary

Dimension	Study 1: Field Experiment	Study 2: Operator-Perception Survey
Integration Point	Chapter 6: Synthesis of operational and operator user-experience evidence into integrated socio-technical explanation (RO3)	

Together, these complementary quantitative methods generate causal evidence on operational effects (Study 1) and explanatory evidence on operator user-experience mechanisms (Study 2), enabling the integrated socio-technical interpretation developed in Chapter 6 (Morse, 2003; Creswell, 2015).

3.5 RESEARCH STRATEGY

The research employs two complementary strategies within the multi-method quantitative design: a quasi-experimental field study (Study 1) and a cross-sectional survey (Study 2). Each is selected to address a specific evidence requirement that the other cannot deliver.

Study 1: Quasi-Experimental Field Strategy

Study 1 estimates the causal effect of rtBRMS on operational performance under authentic operational conditions (Shadish, Cook and Campbell, 2002). A quasi-experimental design is necessitated by the impossibility of random assignment in live airport operations: flights cannot be randomly allocated to gates with and without rtBRMS without disrupting operational integrity, creating passenger confusion, or raising safety concerns, and airport operators would not accept random assignment that could compromise commercial performance (Schultz, 2018; EUROCONTROL, 2017; Kim, Barnhart and Clarke, 2017). Quasi-experimental designs with statistical control are the established alternative in airport operations research, where they have been used to evaluate capacity expansions, air traffic management interventions, and ground-handling innovations (Evler et al., 2022; Kim, Barnhart and Clarke, 2017).

The study leverages naturally occurring variation in rtBRMS deployment across flights, gates, and time periods, to ensure comparability of treatment and control flights on observable characteristics, within-stratum covariate adjustment via Type-III General Linear Models for continuous outcomes, and Firth-penalised logistic regression for the binary fast-process KPIs to handle complete separation (Firth, 1993; Imbens and Rubin, 2015). The field setting is essential for ecological validity: airport gate operations exhibit operational heterogeneity, temporal dependencies, and complex interactions among passengers, staff, aircraft, and infrastructure that laboratory simulations cannot replicate (Steffen, 2008; Jaehn and Neumann, 2015). The design therefore prioritises ecological validity while managing threats to internal validity through statistical technique rather than experimental control.

Study 2: Cross-Sectional Survey Strategy

Study 2 measures latent operator user-experience constructs (perceived predictability, usefulness, situation-awareness support, engagement, performance, productivity, satisfaction) through validated psychometric scales and tests structural relationships among them via PLS-SEM (Hair, Hult, Ringle and Sarstedt, 2022; DeVellis, 2017). A survey is appropriate because these constructs cannot be directly observed and must be inferred from patterns in self-reported perceptions; multi-item scales support construct validity and reliability while enabling simultaneous estimation of measurement and structural models (DeVellis, 2017; Hair et al., 2022).

The cross-sectional design is appropriate because the objective is to identify predictive relationships at a single point in time rather than to track longitudinal changes (Shmueli, 2010; Hair et al., 2019). A longitudinal design would provide stronger evidence for temporal precedence but is infeasible at this stage given access constraints in the operational environment; the cross-sectional approach is therefore treated as a first step in theory development, with the limitation acknowledged in Section 3.12. Online administration enables efficient collection of a large operator sample, automated quality checks, and minimised participant burden (Dillman, Smyth and Christian, 2014); attention checks and reverse-coded items detect careless responding (Meade and Craig, 2012).

3.6 TIME HORIZON

Both studies adopt a cross-sectional time horizon. Study 1 compares treated and control flights observed within a six-month observation window at Mashhad International Airport (MHD); Study 2 collected survey data from frontline operators over a three-week window beginning approximately three months after the close of Study 1, allowing operator perceptions to stabilise around routine rtBRMS use rather than novelty reactions. The cross-sectional design enables efficient data collection and structural estimation but cannot establish temporal precedence; this limitation is acknowledged in Section 3.12 (Saunders, Lewis and Thornhill, 2019; Hair, Hult, Ringle and Sarstedt, 2022).

3.7 STUDY 1: OPERATIONAL IMPACT ESTIMATION

Study 1 estimates the causal effect of rtBRMS on operational performance under authentic operational conditions. The investigation requires rigorous causal inference in a complex field setting characterised by operational heterogeneity, temporal dependencies, and the impossibility of random assignment (Shadish, Cook and Campbell, 2002; Kim, Barnhart and Clarke, 2017). This section sets out the causal framework, design, measurement, statistical specification, and validity safeguards.

3.7.1 Theoretical Foundation and Causal Mechanism

The literature on boarding dynamics and turnaround control consistently shows that the gate process becomes unstable when arrival flow into the aisle is bursty or when cross-flows form in shared corridors, because such patterns lengthen blocking sequences and amplify variability in elapsed times (Steffen and Hotchkiss, 2012; van den Briel, Villalobos, Hogg, Lindemann and Mulé, 2005; Bachmat et al., 2009). Two complementary tactics follow. Pacing the release at the door aligns inflow with the aisle's effective service capacity, smoothing the stream of passengers entering the cabin. Topology-aware routing prevents or postpones merges in the gate-area corridors so that independent streams do not block one another before they reach the aircraft door. Together, these tactics suppress

variance where it forms and therefore narrow boarding and deboarding windows while reducing total Gate Occupation Time (Jaehn and Neumann, 2015).

The fundamental challenge is to estimate the counterfactual: what would have happened to treated flights had they not received rtBRMS. Following the potential outcomes framework (Rubin, 1974; Holland, 1986), for each flight i the treatment effect is $\tau_i = Y_{1i} - Y_{0i}$, where Y_{1i} is the outcome under rtBRMS and Y_{0i} the outcome under legacy coordination; only one of these two potential outcomes is observed for any flight. The average treatment effect on the treated is identified from observational data under the conditional independence assumption $(Y_{1i}, Y_{0i}) \perp T_i \mid X_i$ (Imbens and Rubin, 2015). This assumption is supported by the fact that gate allocation at the study airport is determined by observable operational factors (aircraft type, scheduled turnaround, time of day, passenger load, ground handler) rather than by anticipated turnaround difficulty, and residual confounding from observed covariates is removed within strata through Type-III GLM with covariate adjustment.

3.7.2 Research Design and Moderating Conditions

The quasi-experimental design uses three coordinated strategies to approximate the counterfactual (Shadish, Cook and Campbell, 2002; Angrist and Pischke, 2009) (see Figure 3.1). First, balance on observable operational characteristics is achieved by design rather than post-hoc matching, through a fully-crossed 48-stratum field design in which 171 flights are distributed across four gate topologies × three temporal periods × two day types × two flight types; treatment and control flights are compared within each stratum so that the principal sources of confounding (gate architecture, time of day, day type, and flight type) are held constant by construction. Second, residual confounding from observed covariates within each stratum is removed through within-stratum covariate adjustment: Type-III General Linear Models with covariate adjustment for passenger count, shared access points, and self-check-in availability for the continuous outcomes (Gate Occupation Time S1-H1, boarding window S1-H2a, deboarding window S1-H2b, throughput S1-H3, and the architectural-complexity and load moderation tests S1-H4 and S1-H5), and Firth-penalised logistic regression for the binary fast-process KPIs (S1-H6a FastBoard ≤ 13 min;

S1-H6b FastDeboard ≤ 11 min), the latter chosen specifically to handle the complete separation observed in the deboarding model (Firth, 1993). Third, robustness of the treatment-effect estimate is assessed through Welch's unequal-variance t-tests as an assumption-free comparison of means, Cohen's d and partial η^2 for transparent effect-size disclosure, and sensitivity analyses with covariate dropping and stratum-restricted samples to confirm that the results are not artefacts of estimator choice.

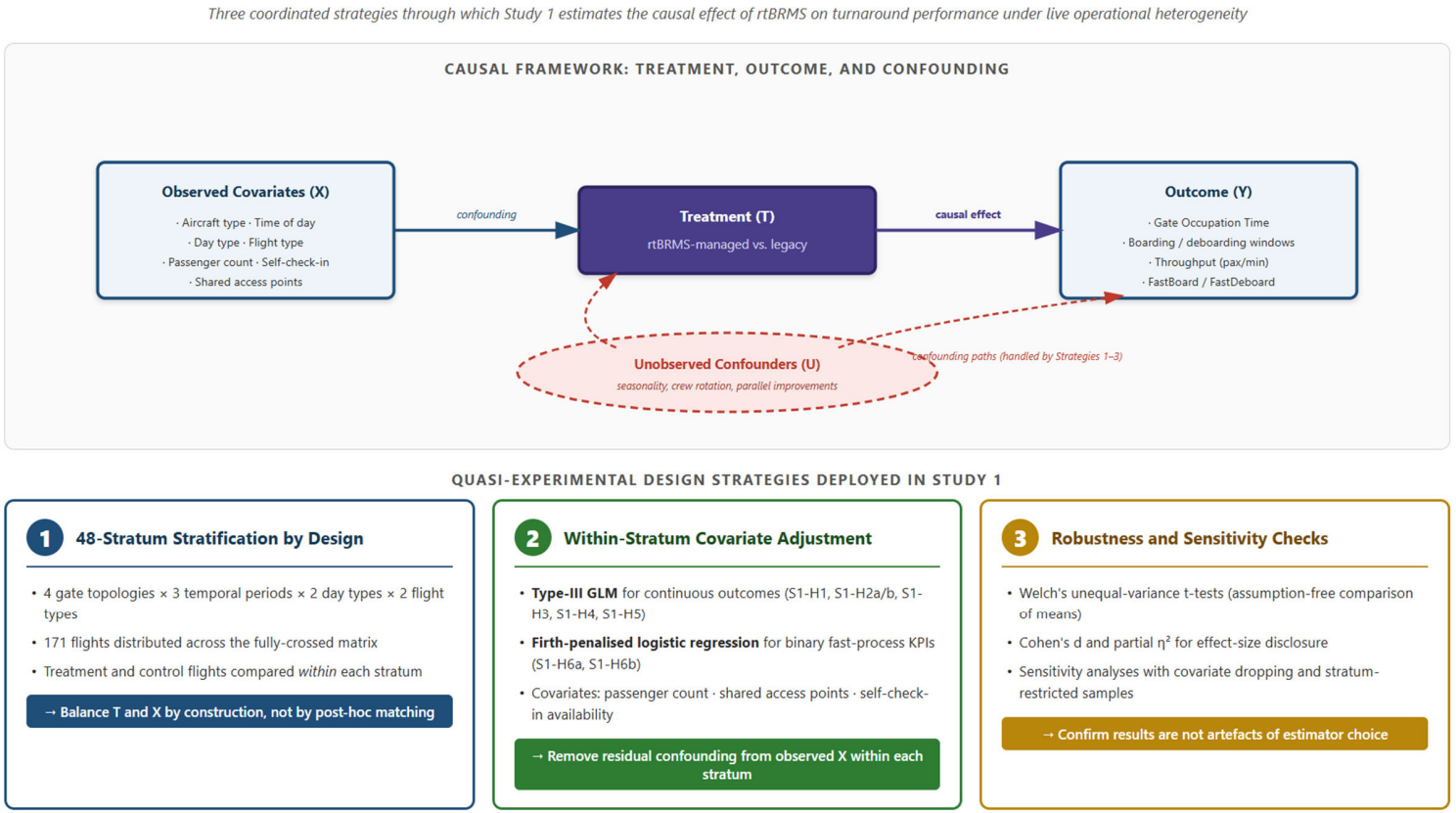


Figure 3-1 Causal Framework: Treatment, Outcome, and Confounding

Note: The top panel shows the standard causal-inference diagram in which observed covariates (X) confound the treatment–outcome relationship (T → Y) and unobserved confounders (U) create additional non-identifiable paths. The three strategies in the bottom panel jointly address these threats: stratification by design balances T and X across 48 cells before estimation; within-stratum covariate adjustment via Type-III GLM and Firth-penalised logistic regression removes residual confounding from observed X; and robustness checks via Welch t-tests, effect-size disclosure (Cohen's d, partial η^2), and sensitivity analyses confirm that the results are not artefacts of estimator choice. Adapted from Shadish, Cook and Campbell (2002) and Angrist and Pischke (2009).

Moderators and Boundary Conditions

The effectiveness of the execution-layer mechanism is contingent on several factors. First, physical topology around the gate: where access to the aircraft is shared or where corridors merge, structural interference is intrinsically higher. In such layouts, topology-aware routing prevents otherwise inevitable cross-flows, so the marginal return to routing control rises with architectural complexity (Ferrari & Nagel, 2005).

Second, passenger load and its proximate correlates: as congestion increases, boarding time becomes increasingly sensitive to bursty arrivals because long blocking chains form behind a few slow events. Under those circumstances, pacing is not merely advantageous but necessary, and the benefit of pacing is increasing in load and in the heaviness of aisle-clearing-time tails (Bachmat et al., 2009; Jaehn & Neumann, 2015).

Third, data-quality governance: where event-log and milestone data are complete, time-synchronised, and accurate, estimates of conformance and operational KPIs are more reliable, which supports clearer attribution of observed effects to the execution-layer mechanism (Rott, Schultz and Fricke, 2023).

3.7.3 Operational Measurement Model

The measurement model operationalises the mechanism and outcomes using indicators sensitive to the changes the controller induces. To verify that pacing actually occurs, the model uses three signatures in the door-area data: the variability of inter-arrival times to the aircraft door, the distribution of release-burst sizes, and the frequency with which rules trigger within fixed windows. A successful pacing regime lowers variability, limits burst size, and exhibits consistent rule activity during surge periods (Steffen & Hotchkiss, 2012; Bachmat et al., 2009).

Routing control is captured by the share of conflict-free paths through the gate corridors, by the number of prevented merges relative to an unregulated baseline, and by occupancy measures at predicted merge horizons. Improvements on these indicators demonstrate that the controller removes cross-flow interactions before they materialise (van den Briel, Villalobos, Hogg, Lindemann & Mulé, 2005).

Operational performance is indexed by the standard deviation of boarding and deboarding windows and by Gate Occupation Time. The theory predicts that as inflow variance is suppressed and cross-flows are eliminated, windows tighten and the aircraft vacates the gate earlier and more reliably (Steffen & Hotchkiss, 2012).

3.7.4 Threats to Validity and Design Countermeasures

A first threat is attribution bias: improvements could coincide with staffing changes, altered gate-assignment practices, or seasonal schedule shifts rather than the execution-layer mechanism itself. To protect against this, the design specifies a difference-in-differences approach with staggered activation across gates, flights, or day-parts, combined with fixed effects for the ground handler, aircraft type, and schedule mix (Dorndorf, Jaehn & Pesch, 2016).

A second threat is measurement error in event logs, including timestamp misalignment across systems and occasional sensor noise in corridor-state detection. The countermeasure is methodological triangulation: audit samples of manual timings are used to assess bias in automated records, while analyses apply sensor-confidence filters and robustness checks (Rott, Schultz and Fricke, 2023).

A third threat is common-method variance when user-experience constructs are collected from the same respondents at the same time. The design therefore separates measurements temporally, uses multiple sources for outcomes, and links perceptions to independent operational data (Christian, Garza & Slaughter, 2011).

3.7.5 Data Collection and Operational Context

Data collection occurs at Mashhad International Airport (MHD), an operational international airport serving predominantly short-haul domestic and regional routes, where rtBRMS is deployed as a pilot system across selected gates and time periods. The selection of this research site is justified by several considerations. First, the airport handles a high volume of short-haul turnarounds with operational characteristics, tight scheduling,

narrow-body aircraft, variable passenger loads, and multi-stakeholder coordination, that are representative of the operational challenges rtBRMS is designed to address (Schultz, 2018). Second, the airport's gate infrastructure encompasses multiple topology types (single-access, shared-area, and multi-access configurations), providing the architectural heterogeneity required by the 48-stratum design. Third, the researcher's institutional access to the airport enabled deployment of the rtBRMS pilot system, direct extraction of event-log data, and coordination with ground handling staff for operational data collection, conditions that would be difficult to replicate at airports without an established research partnership (Kim, Barnhart and Clarke, 2017).

Operational Characteristics

The operational context is characterised by high-frequency turnarounds, tight scheduling constraints, and significant passenger flow variability, making it representative of the operational challenges that rtBRMS is designed to address (Kim, Barnhart and Clarke, 2017). The airport serves primarily domestic routes using narrow-body aircraft with typical passenger loads of 120–180 passengers and scheduled turnaround times ranging from 25 to 60 minutes depending on aircraft type and route characteristics. Gate infrastructure includes four topology types of increasing architectural complexity (Type 1 through Type 4, as defined in Table 3.2), providing the structural variation required to test the moderation hypothesis S1-H4 regarding the interaction between rtBRMS effectiveness and gate complexity.

Observation Period and Sample Size

The observation period captures 171 flights across treatment (rtBRMS-enabled) and control (legacy coordination) conditions, distributed across the 48 strata defined by gate topology, temporal period, day type, and flight type. This sample size reflects the operational reality of the pilot deployment: rtBRMS was activated on selected gates during defined time windows, with remaining flights at the same gates operating under standard procedures to serve as within-gate controls (Shadish, Cook and Campbell, 2002). Power analysis for the primary outcome variable (GOT) indicates that with 171 flights and the observed effect sizes, the study achieves adequate statistical power for detecting practically

meaningful differences using Welch t-tests and General Linear Models with Type III sums of squares, particularly given the variance reduction achieved through stratification and covariate adjustment (Cohen, 1988). The stratified design concentrates statistical power within operationally homogeneous strata, reducing residual variance and improving the precision of treatment effect estimates relative to an unstratified comparison of equivalent total sample size (Shadish, Cook and Campbell, 2002).

Stratified Design Structure

The study employs a stratified experimental design to systematically vary operational conditions and assess rtBRMS effectiveness across diverse scenarios. The design structure is organised around four key dimensions that capture the primary sources of operational heterogeneity (see Table 3.2): gate tunnel type, time of day, day type, and flight type. This stratification ensures that treatment effects are estimated across the full range of operational conditions encountered in practice, enhancing external validity and identifying boundary conditions where rtBRMS effectiveness may vary (Shadish, Cook and Campbell, 2002).

The rationale for adopting a stratified design rather than a simple treatment-versus-control comparison rests on a fundamental characteristic of airport gate operations: operational heterogeneity. A flight's turnaround performance is not determined solely by whether rtBRMS is active but is jointly shaped by the physical environment in which the turnaround occurs, the temporal demand context, the day type, and the procedural complexity of the flight type. Gate topology matters because different access configurations create fundamentally different interference patterns and baseline variability levels, meaning that the baseline GOT variance differs substantially across gate types before any intervention is applied (Schultz, 2018). Temporal period matters because morning peak, midday, and evening/night operations exhibit distinct demand patterns, staffing levels, and accumulated delay profiles, each creating a distinct operational context in which rtBRMS must function (Kim, Barnhart and Clarke, 2017). Day type matters because weekday and weekend operations differ in passenger composition, schedule density, and operational tempo. Flight type matters because international flights involve

customs, immigration, and security protocols that change the baseline turnaround envelope relative to domestic flights (ICAO, 2018; Eurocontrol, 2017).

If these sources of heterogeneity were ignored and all 171 flights were pooled into a single treatment-versus-control comparison, the estimated treatment effect would represent an average across fundamentally different operational contexts, an average that would not accurately describe rtBRMS effectiveness in any specific context, would conflate system effects with contextual variation, and would risk under-stating effects in conditions where rtBRMS matters most while over-stating them in conditions where it is largely irrelevant.

The 48-stratum design (4 gate topologies × 3 temporal periods × 2 day types × 2 flight types) solves this problem in two ways. First, it ensures that treatment and control flights are compared within operationally homogeneous cells, so that the estimated effect within each stratum reflects the genuine causal impact of rtBRMS under those specific conditions rather than a confounded mixture of system effects and contextual differences. Second, it enables the detection of treatment-effect heterogeneity, the possibility that rtBRMS produces large GOT reductions at complex shared-area gates during peak periods but smaller effects at simple single-access gates during off-peak periods, which is essential for practitioners who need to know not just whether the system works on average but where and when it works most effectively (Shadish, Cook and Campbell, 2002).

Table 3-2 48-Stratum Design Overview (1)

Dimension	Levels	Notes
Gate_Tunnel Type	Type1: single-access 2–3 doors; Type2: single-access ≥4 doors; Type3: shared-area single-access; Type4: shared-area multi-access ≥4 doors	Structural complexity increments across types

Dimension	Levels	Notes
Time_of_Day	Morning peak; Midday; Evening/Night	Circadian operational bands
Day_Type	Weekday; Weekend	Operational rhythm differences
Flight_Type	Domestic; International	Procedural diversity

The full factorial combination of these dimensions yields 48 distinct strata (4 × 3 × 2 × 2), each representing a unique operational scenario. Table 3.3 summarizes the factor cardinalities and their theoretical justification.

Table 3-3: Theoretical Justification for 48-Stratum Design Overview

Factor	Cardinality	Theoretical Justification
Gate Topology (Gate_Tunnel Type)	4	Gate topology determines the potential for cross-flow interference. Simple topologies with single corridors minimize structural interference, while complex topologies with shared or merging corridors create opportunities for rtBRMS routing control to prevent conflicts (Ferrari & Nagel, 2005). The four-level classification captures increasing architectural complexity: Type1 represents basic single-access gates with 2-3 doors, Type2 extends to single-access with 4+ doors, Type3 introduces shared-area complexity with single access, and Type4 represents

Factor	Cardinality	Theoretical Justification
		the most complex configuration with shared areas and multiple access points.
Time_of_Day	3	Temporal bands reflect circadian operational patterns that influence passenger behavior, staff availability, and system load. Morning peak periods (typically 06:00-10:00) exhibit high passenger volumes and tight scheduling, midday periods (10:00-17:00) show moderate and variable demand, while evening/night periods (17:00-06:00) present distinct operational characteristics including reduced staffing and different passenger demographics. These temporal variations affect both baseline performance and the potential for rtBRMS to deliver improvements.
Day_Type	2	Weekday versus weekend operations exhibit fundamentally different operational rhythms, passenger compositions, and scheduling patterns. Weekdays typically feature business travelers, tighter schedules, and higher operational tempo, while weekends show more leisure travelers, relaxed schedules, and different flow patterns. This distinction is critical for assessing whether rtBRMS effectiveness varies with operational context and passenger characteristics.
Flight_Type	2	Domestic and international flights differ substantially in procedural requirements, passenger processing complexity, and turnaround constraints. International flights involve customs, immigration, security protocols, and typically longer turnaround times, while domestic flights feature streamlined procedures and tighter turnaround windows. These procedural differences create distinct operational environments that may moderate rtBRMS effectiveness, as the system must adapt to varying regulatory and operational constraints.

Key Performance Indicators and Thresholds

The study employs eight key performance indicators (KPIs) to assess rtBRMS effectiveness across multiple dimensions of operational performance. These KPIs are selected based on their theoretical relevance, practical importance, and data availability in A-CDM systems (Table 3.4). Each KPI is operationalized with specific definitions and performance thresholds that distinguish acceptable from unacceptable outcomes, enabling both continuous and categorical analysis of treatment effects (EUROCONTROL, 2017).

Table 3-4 KPI Definitions and Thresholds

KPI	Definition	Threshold	Used in S1 hypothesis
Gate Occupation Time (GOT)	Elapsed time from aircraft arrival at gate (AIBT) to departure from gate (AOBT)	Continuous; lower is better	S1-H1, S1-H4, S1-H5
Boarding Window	Elapsed time from boarding start to boarding completion	Continuous; lower is better	S1-H2a
Deboarding Window	Elapsed time from door opening to last passenger exit	Continuous; lower is better	S1-H2b
Boarding Throughput	Passengers per minute during boarding	Continuous; higher is better	S1-H3
Deboarding Throughput	Passengers per minute during deboarding	Continuous; higher is better	S1-H3
FastBoard	Boarding completes within ≤13 minutes	Binary	S1-H6a
FastDeboard	Deboarding completes within ≤11 minutes	Binary	S1-H6b

These KPIs collectively capture the multidimensional nature of turnaround performance, encompassing total stand time (GOT), the temporal envelopes of the two passenger-flow phases (boarding and deboarding windows), the intensive flow rate of each phase (throughput), and binary attainment of operationally critical fast-process thresholds (FastBoard ≤13 min; FastDeboard ≤11 min). The fast-process thresholds correspond to high-performance benchmarks reported in the airport-operations literature (Schultz, 2018; Tang et al., 2025) and align with internal performance targets at the study airport.

3.7.6 Statistical Analysis Methods

The statistical analysis combines three estimators chosen to match the data structure of an unbalanced field design with unequal variances and binary fast-process outcomes. For continuous outcomes (GOT, boarding window, deboarding window, throughput), unadjusted comparisons of legacy and rtBRMS conditions use Welch's t-tests, which provide valid inference under unequal variances and unbalanced group sizes (Welch, 1938). Covariate-adjusted estimates use General Linear Models with Type III sums of squares, the standard framework for partial hypothesis tests in unbalanced factorial designs (McCullagh and Nelder, 1989; Fox, 2016), with covariates including passenger count, flights per gate per day, shared access points, and self-check-in availability. Estimated marginal means with Bonferroni-corrected pairwise contrasts report covariate-adjusted treatment effects and control family-wise error across multiple comparisons (Hair et al., 2022). Effect magnitudes are quantified using Cohen's d for unadjusted contrasts and partial η^2 for GLM terms (Cohen, 1988).

For binary fast-process outcomes (FastBoard ≤13 min; FastDeboard ≤11 min), the analysis uses logistic regression with the same set of operational covariates (Hosmer, Lemeshow and Sturdivant, 2013). Where complete or quasi-complete separation arises in the binary data, Firth's penalised maximum likelihood is applied to produce finite, bias-reduced odds ratios that avoid the infinite estimates generated by standard maximum likelihood under separation (Firth, 1993; King and Zeng, 2001).

Robustness is assessed through three checks: re-estimation of the continuous outcomes under heteroscedasticity-consistent standard errors; comparison of unadjusted and covariate-adjusted treatment effects to identify covariate-driven shifts; and re-estimation of the binary fast-process models under Firth's penalised maximum likelihood with covariate dropping and stratum-restricted samples to confirm that the rtBRMS coefficient is not an artefact of estimator choice (Firth, 1993). Diagnostics include Variance Inflation Factors for collinearity, residual-fit plots for homoscedasticity, and influence statistics (leverage, Cook's distance) for high-leverage observations.

3.7.7 Study 1 - Hypotheses Operationalisation and Statistical Specification

The hypotheses in Study 1 (S1-H1 through S1-H6b) were developed in Section 2.11 based on the queueing-theoretic, TOC, and A-CDM foundations established in the literature review. Table 3.5 operationalises these hypotheses by specifying dependent variables, independent variables, covariates, and statistical model specifications.

Table 3.5 aligns hypotheses, dependent and independent variables, model specifications, and the intended effect-size and fit metrics. Positioning it at the end of the analysis-plan subsection transforms it into an implementation checklist that links designs to estimators, anticipates separation in logistic models, and clarifies where heteroscedasticity-robust inferences and trimmed-mean checks enter the workflow (Welch, 1938; Nelder and Wedderburn, 1972).

Table 3-5 Hypotheses Statistical Summary

Hypothesis (H1-H6)	Type of Data & Measures	Dependent Variable(s)	Independent Variable(s) & Covariates	Analysis & Model Spec
S1-H1 – rtBRMS_Enabled main effect on GOT	Flight-level (171 flights), event-derived. Measure: GOT_min (min).	GOT_min	IV: rtBRMS_Enabled (0/1). Covariates: Passenger_Count; Flights_per_Gate_per_Day; Shared_Access_Points; Self_Checkin_Used.	Independent t-test; GLM UNIANOVA (Type III SS); EMMEANS (Bonferroni).
S1-H2 – Window efficiency	Flight-level. Measures: Deboard_Window_min; Board_Window_min (min).	Deboard_Window_min; Board_Window_min	IV: rtBRMS_Enabled. Covariates (GLM): Passenger_Count; Shared_Access_Points.	t-tests; GLM with covariates; Bonferroni pairwise.
S1-H3 – Throughput performance	Flight-level throughput from event logs. Measures: Throughput_deboard_pax_min; Throughput_board_pax_min (pax/min).	Throughput_deboard_pax_min; Throughput_board_pax_min	IVs: rtBRMS_Enabled; Self_Checkin_Used. Covariates: Shared_Access_Points; Passenger_Count.	t-tests; GLMs (Type III SS) per throughput; EMMEANS.
S1-H4 – Structural interaction	Flight-level GOT by gate architecture. Measures: GOT_min; Gate_Type (1..4).	GOT_min	rtBRMS_Enabled × Gate_Type; Covariates: Passenger_Count; Flights_per_Gate_per_Day;	GLM (Type III SS) with interaction; EMMEANS by Gate_Type; Bonferroni contrasts.

Hypothesis (H1-H6)	Type of Data & Measures	Dependent Variable(s)	Independent Variable(s) & Covariates	Analysis & Model Spec
			Shared_Access_Points; Self_Checkin_Used.	
S1-H5 – Load interaction & temporal robustness	Flight-level GOT with continuous load & quartiles. Measures: Passenger_Count; Load_Quartile; Time_of_Day; Day_Type.	GOT_min	rtBRMS × Passenger_Count/Load_Quartile; Time_of_Day; Day_Type.	Factorial GLM (Type III SS) with continuous load + quartile factor; EMMEANS Bonferroni; profile plots.
S1-H6a, S1-H6b – Fast-process KPIs	Flight-level binary KPIs from process durations. Measures: FastBoard_min (≤13); FastDeboard_min (≤11).	FastBoard_min; FastDeboard_min	IVs: rtBRMS_Enabled; Gate_Type; Time_of_Day; Day_Type; Flight_Type; Passenger_Count; Flights_per_Gate_per_Day; Shared_Access_Points; Self_Checkin_Used.	Binary logistic regression (odds ratios, 95% CIs, Wald p-values) with classification accuracy and predicted probabilities; Firth's penalised maximum likelihood applied where complete or quasi-complete separation arises (Firth, 1993).

3.8 STUDY 2: OPERATOR MECHANISM INVESTIGATION

3.8.1 Research Design and Hypothesis Coverage

Study 2 tests the twenty-five operator user-experience hypotheses derived in Section 2.11.3 (S2-H1 through S2-H17) using a cross-sectional PLS-SEM survey of 224 frontline operators at Mashhad International Airport. The design is cross-sectional and predictive rather than explanatory, consistent with PLS-SEM's predictive ethos and out-of-sample evaluation logic (Shmueli, 2010; Shmueli et al., 2019; Hair et al., 2022). The four theoretical frameworks underpinning the model, human-automation interaction (Lee and See, 2004), JD-R (Bakker and Demerouti, 2007), TAM2 (Venkatesh and Davis, 2000), and IS Success (DeLone and McLean, 2003), were specified in Section 2.7 and converted into the structural model in Section 2.11.2.

The hypothesis set is operationalised as follows:

- **S2-H1** (FSP → PSP) is tested through the path from the four formative FSP indicators to the four reflective PSP indicators.

- **S2-H2a / S2-H2b** (AUT → PSP, AUT → ENG) are tested through the autonomy block (three reflective indicators) and its two outgoing paths.

- **S2-H3a / S2-H3b / S2-H3c** (PSP → PPC, PSP → ENG, PSP → SS) are the three downstream paths from the cognitive intervening construct.

- **S2-H4a / S2-H4b** (JSR → PPC, JSR → ENG) capture the JD-R reduced-demands pathway.

- **S2-H5a / S2-H5b** (CSR → PPC, CSR → IWP) test the formative comparative-superiority composite.

- **S2-H6 through S2-H9b** specify the intervening construct-to-consequence chain (PPC → ENG, ENG/PPC → IWP, PPC/IWP → EMP, ENG/IWP → SS, EMP → SS).

- **S2-H10 through S2-H17** are the eight moderation hypotheses, tested through the two-stage PLS-SEM moderation procedure (Hair et al., 2022) using passenger type, interaction frequency, level of responsibility, years of experience, operational area, role, and flights per shift as moderators on the FSP→PSP, PPC→EMP, IWP→EMP, and EMP→SS pathways.

3.8.2 Sampling and Data Collection

The target population of this study is based on frontline airport staff directly involved in turnaround operations at gates equipped with rtBRMS, including ground handling coordinators, gate agents, and operations supervisors (Schultz, 2018). These roles are selected because they have direct exposure to rtBRMS outputs, responsibility for coordinating passenger flow, and influence over turnaround performance (Kim, Barnhart and Clarke, 2017). Critically, all participants are active users of rtBRMS rather than external observers; their evaluations are therefore post-use perceptions in the sense of Bhattacherjee's (2001) post-acceptance framework and the experienced-user formulation of TAM2 (Venkatesh and Davis, 2000), which presuppose actual utilisation as the basis for the perceived-usefulness, predictability, and satisfaction judgements that the structural model estimates. The sampling frame is constructed from employee rosters provided by the airport operator and ground handling companies, ensuring comprehensive coverage of the target population (Saunders, Lewis and Thornhill, 2019).

The study employs stratified random sampling to ensure representation across job roles, experience levels, and shift patterns (Bryman, 2016). Stratification variables include job role (coordinator, agent, supervisor), experience (< 2 years, 2-5 years, > 5 years), and shift (morning, afternoon, evening), with proportional allocation to maintain population representativeness (Cochran, 1977). The target sample size of 200 was set on the basis of the Kang's theory (2021), and Hair et al. (2022) minimum-sample-size guideline for PLS-SEM, which requires at least ten times the maximum number of arrows directed at any single latent variable in the structural model. With at most four arrows pointing at any one construct in the proposed model (e.g., the FSP / AUT / PSP / JSR predictors of PPC), the heuristic minimum is 40, and the target of 200 provides a comfortable margin for

moderation analysis and bootstrap stability. The final usable sample comprised 224 valid responses after excluding incomplete submissions.

Data collection occurs through an online survey administered via secure web platform, with email invitations sent to sampled employees containing unique access links (Dillman, Smyth and Christian, 2014). The survey is available in English and Farsi to accommodate the linguistic profile of the operational staff at the study airport, with translations validated through forward-backward translation, expert-panel reconciliation, cognitive interviews, and pilot testing (Brislin, 1970; Beaton et al., 2000), as detailed in Section 4.3.6. The survey was open for three weeks (9–30 March 2026), with reminders distributed at shift handovers at weekly intervals to maximise response rates while reaching personnel with limited email access (Dillman, Smyth and Christian, 2014). Participation is voluntary and anonymous, with informed consent obtained electronically before survey access (Saunders, Lewis and Thornhill, 2019).

3.8.3 Measurement Model: Constructs and Indicators

The measurement model specifies how latent constructs are operationalized through observable indicators, distinguishing between reflective and formative measurement approaches (Hair, Hult, Ringle and Sarstedt, 2022). Reflective indicators are manifestations of underlying constructs, sharing common variance and exhibiting high intercorrelations (Jarvis, MacKenzie and Podsakoff, 2003). Formative indicators are defining characteristics that collectively constitute constructs, potentially exhibiting low intercorrelations and non-interchangeability (Diamantopoulos and Winklhofer, 2001). The study employs both reflective and formative measurement approaches depending on the theoretical nature of each construct, as detailed in Table 3.6.

Table 3.6 presents the measurement type classification for all variables in the study, distinguishing between reflective and formative specifications Eight operator user-experience constructs (PSP, ENG, PPC, IWP, EMP, SS, AUT, JSR) are measured reflectively because they represent latent operator user-experience states that cause observable item responses; two constructs (FSP and CSR) are measured formatively as

composites whose four indicators each capture distinct, non-interchangeable defining facets of the construct. In contrast, CSR is measured formatively as a composite of distinct system superiority facets, while contextual variables (Q12-Q18) are formative single indicators representing externally determined conditions rather than manifestations of latent traits. This classification follows established guidelines in PLS-SEM literature for distinguishing measurement model types based on the direction of causality between constructs and indicators (Hair, Hult, Ringle and Sarstedt, 2022).

The classification of each construct as reflective or formative follows the four-criterion decision protocol established by Jarvis, MacKenzie and Podsakoff (2003) and endorsed in PLS-SEM methodology by Hair, Hult, Ringle and Sarstedt (2022). The first criterion is the direction of causality between the construct and its indicators: in reflective models, the latent construct causes the observed indicators, meaning that a change in the construct produces corresponding changes in all indicators simultaneously; in formative models, the indicators cause the construct, meaning that a change in any single indicator alters the composite score regardless of whether other indicators change (Diamantopoulos and Winklhofer, 2001). The second criterion is interchangeability: reflective indicators are interchangeable because they share a common theme and tap the same underlying domain, so dropping one indicator does not fundamentally alter what the construct represents; formative indicators are not interchangeable because each captures a distinct facet of the construct, and dropping one indicator removes a defining component that changes the construct's meaning (Jarvis, MacKenzie and Podsakoff, 2003). The third criterion is covariation: reflective indicators should covary because they are jointly caused by the same latent variable, whereas formative indicators need not covary because they represent independent causal inputs that may vary independently of one another (Hair, Hult, Ringle and Sarstedt, 2022). The fourth criterion concerns the nomological network: reflective indicators share the same antecedents and consequences because they are manifestations of the same construct, whereas formative indicators may have different antecedents and consequences because they represent conceptually distinct dimensions (Jarvis, MacKenzie and Podsakoff, 2003). Applying these four criteria systematically to each construct in the proposed model yields the classifications presented in Table 3.6. For the eight reflective

constructs (PSP, AUT, JSR, ENG, PPC, IWP, EMP, SS), the indicators represent interchangeable manifestations of a single latent psychological state: an operator who experiences high work engagement, for example, would be expected to rate all UWES-3 items consistently high, and removing any single item would not alter the meaning of the construct. For the two formative composites (FSP and CSR), the indicators represent distinct, non-interchangeable facets that collectively define each construct, as detailed below.

Table 3-6 Reflective vs. Formative Measurement Types

Variable	**Measurement Type**	**Justification Summary**
Flow Stability Perception (FSP)	Formative composite	FSP is specified as a formative composite because its four indicators capture distinct operational dimensions of stabilised passenger flow (smoothness, surge absence, process smoothness, pacing consistency) that together define flow stability rather than reflecting it. Each indicator contributes a unique dimension; removing one would alter the meaning of the construct (Diamantopoulos and Winklhofer, 2001; Hair, Hult, Ringle and Sarstedt, 2022).
Perceived System Predictability (PSP)	Reflective	Cognitive belief that causes consistent evaluative items; indicators covary and represent the same underlying perception.
Work Engagement (ENG)	Reflective	Based on UWES theory: engagement (state) causes vigor, dedication, absorption; indicators are effects of a latent condition.
Perceived Performance Contribution (PPC)	Reflective	Perceived contribution influences multiple evaluative items, which are manifestations of the same underlying appraisal.

Variable	Measurement Type	Justification Summary
Individual Work Performance (IWP)	Reflective	A latent performance capability expressed through correlated self-reported work behavior indicators.
Employee Productivity (EMP)	Reflective	A general perception of productivity improvement that causes several correlated evaluative items.
System Satisfaction (SS)	Reflective	Satisfaction is an attitude that produces multiple interchangeable evaluative indicators of overall approval.
Perceived Autonomy (AUT)	Reflective	Autonomy is a operator user-experience state that manifests in item responses; widely modeled reflectively in JD-R research.
Job Stress Reduction (JSR)	Reflective	Reduced stress is a latent operator user-experience experience that leads to consistent perceptions across indicators.
Comparative Superiority of rtBRMS (CSR)	Formative composite	CSR is specified as a formative composite because its four indicators capture conceptually distinct dimensions of system superiority that are not interchangeable and do not share a common cause. CSR1 captures ease of gate management (operational simplicity), CSR2 captures time efficiency (speed of execution), CSR3 captures inter-stakeholder coordination quality (cross-functional smoothness), and CSR4 captures overall performance improvement (global evaluation). Applying the Jarvis, MacKenzie and Podsakoff (2003) criteria: (1) Direction of causality: the indicators define the construct rather than being caused by it, an operator's overall judgement of comparative superiority is formed from

Variable	Measurement Type	Justification Summary
		these distinct facets rather than causing them; (2) Interchangeability: the indicators are not interchangeable, an operator could perceive rtBRMS as faster (CSR2) but not better for coordination (CSR3), meaning that removing the coordination facet would change what 'comparative superiority' means; (3) Covariation: the indicators need not covary, improvements in time efficiency do not necessarily imply improvements in coordination quality, because these depend on different operational mechanisms; (4) Nomological network: the indicators have different antecedents, ease of management depends on interface design, time efficiency depends on pacing algorithms, and coordination quality depends on multi-stakeholder integration. Formative validity is assessed through collinearity diagnostics (VIF < 3.3), outer weight significance via bootstrapping, and nomological validity through theoretically expected relationships with PPC and IWP (Hair, Hult, Ringle and Sarstedt, 2022; Diamantopoulos and Winklhofer, 2001).
Role at Airport (Q12)	Formative (single indicator, categorical)	Represents categorical assignment of job function; not caused by a latent trait, but a contextual condition shaping operational activity.
Years of Experience (Q13)	Formative (single indicator, ordinal)	Tenure forms experience; not an effect of a operator user-experience latent variable.
Frequency of Interaction with rtBRMS (Q14)	Formative (single indicator, ordinal)	Represents exposure intensity; an externally determined condition, not a manifestation of a latent construct.

Variable	Measurement Type	Justification Summary
Flights Handled per Shift (Q15)	Formative (single indicator, numerical/ordinal)	Objective operational workload that forms contextual conditions; does not reflect a latent operator user-experience state.
Primary Level of Responsibility (Q16)	Formative (single indicator, categorical)	Role responsibility is an externally defined contextual factor shaping tasks; not interchangeable and does not reflect a latent trait.
Primary Operational Area / Terminal (Q17)	Formative (single indicator, categorical)	Operational area is a structural context variable; determines operational environment rather than reflecting a latent construct.
Primary Passenger Type (Q18)	Formative (single indicator, categorical)	Passenger flow composition forms contextual demand; not an effect of a personal or operator user-experience latent factor.

For the eight reflective constructs, the classification is justified as follows. Each construct represents a latent psychological state that exists independently of its indicators and causes observable item responses: an operator who experiences high work engagement (ENG) would be expected to report high vigour, high dedication, and high absorption simultaneously, because all three are manifestations of the same motivational state (Schaufeli and Bakker, 2004). Similarly, an operator who perceives high system predictability (PSP) would rate all four predictability items consistently, because consistency, anticipation, clarity, and foreseeability are interchangeable expressions of the same cognitive belief about system behaviour (Lee and See, 2004). The same logic applies to AUT (three interchangeable expressions of perceived discretion), JSR (three interchangeable expressions of perceived stress reduction), PPC (three interchangeable expressions of perceived system usefulness), IWP (three interchangeable expressions of perceived task execution quality), EMP (three interchangeable expressions of perceived productivity), and SS (three interchangeable expressions of overall system approval). In

each case, removing one indicator would not alter the meaning of the construct, the indicators should covary because they share a common cause, and the indicators share the same antecedents and consequences within the nomological network, all characteristics that confirm reflective specification according to the Jarvis, MacKenzie and Podsakoff (2003) criteria. Reflective validity is assessed through internal consistency reliability (composite reliability > 0.70, Cronbach's alpha > 0.70), convergent validity (AVE > 0.50), and discriminant validity (HTMT < 0.85, Fornell-Larcker criterion), as detailed in Section 3.8.4 (Hair, Hult, Ringle and Sarstedt, 2022).

The constructs in the proposed model are classified along the orthodox structural-equation-modelling distinction between exogenous and endogenous variables (Kline, 2016; Hair et al., 2022), which determines both the algebraic specification of the model and the way each construct is treated by the SmartPLS estimator. Independent variables (exogenous constructs) are those determined outside the system of equations and which therefore receive no incoming structural arrow; their variance is taken as given and no error term is estimated for them. Flow Stability Perception (FSP), Perceived Autonomy (AUT), Job Stress Reduction (JSR), and Comparative Superiority of rtBRMS (CSR) occupy this position, each functioning as an upstream antecedent grounded in a distinct theoretical tradition: variance suppression and queueing-theoretic stability for FSP, the resource branch of the Job Demands–Resources model for AUT and JSR, and innovation-quality signalling for CSR. Dependent variables (endogenous constructs) are those whose variance is partially explained by other constructs in the model, signalled by at least one incoming structural arrow, an estimated R^2, and an implied error term. Perceived System Predictability (PSP), Perceived Performance Contribution (PPC), Work Engagement (ENG), Individual Work Performance (IWP), Employee Productivity (EMP), and System Satisfaction (SS) are all endogenous in this strict sense; their classification as dependent variables is governed by the arrows that terminate on them and is unaffected by the fact that several of them simultaneously emit arrows to constructs further down the chain. The descriptive labels used elsewhere in the thesis to convey position in the cascade, antecedent, intervening construct, outcome, are heuristic rather than formal; the operative classification used throughout the empirical analysis is the binary independent/dependent

(exogenous/endogenous) distinction reported in Table 3.7, and it is logically independent of the measurement specification (reflective latent versus formative composite) addressed separately in Section 3.8.3 and Table 3.6.

Table 3-7 Role of Variables in Model

Variable	Type	Role in Model	Why Included
Flow Stability Perception (FSP)	Independent variable (exogenous construct); formative composite	Core antecedent	Captures perceived operational stability generated by rtBRMS; represents the primary operator user-experience translation of objective variance suppression (Study 1).
Perceived System Predictability (PSP)	Dependent variable (endogenous construct); reflective latent	Cognitive intervening construct	Reflects the extent to which staff can anticipate system behaviour; theorized as the key cognitive mechanism linking stability to motivation and performance.
Work Engagement (ENG)	Dependent variable (endogenous construct); reflective latent	Motivational intervening construct	Represents energy, enthusiasm, and absorption in work tasks; translates cognitive predictability into behavioural effort.
Perceived Performance Contribution (PPC)	Dependent variable (endogenous construct); reflective latent	Self-evaluative intervening construct	Captures the extent to which rtBRMS is perceived as enhancing individual task effectiveness; reflects system-enabled performance appraisal.

Variable	Type	Role in Model	Why Included
Individual Work Performance (IWP)	Dependent variable (endogenous construct); reflective latent	Proximal behavioural outcome	Measures task-level execution quality and effectiveness in gate operations.
Employee Productivity (EMP)	Dependent variable (endogenous construct); reflective latent	Distal performance outcome	Reflects perceived productivity gains attributable to rtBRMS usage; aligns with organizational efficiency objectives.
System Satisfaction (SS)	Dependent variable (endogenous construct); reflective latent	Final evaluative outcome	Captures overall satisfaction with rtBRMS as a technological support system; represents attitudinal acceptance outcome.
Perceived Autonomy (AUT)	Independent variable (exogenous construct); reflective latent	Resource antecedent	Captures discretion preserved under rtBRMS; predicts PSP and ENG via the JD-R resource pathway.and ENG via JD-R resource pathway.
Job Stress Reduction (JSR)	Independent variable (exogenous construct); reflective latent	Resource antecedent	Captures perceived strain reduction under rtBRMS; predicts PPC and ENG via the JD-R reduced-demands pathway.
Comparative Superiority of rtBRMS (CSR)	Independent variable (exogenous construct); formative composite	Quality-signal antecedent	Captures perceived superiority over legacy coordination as a defining-facet composite; predicts PPC and IWP.

Variable	Type	Role in Model	Why Included
Level of Responsibility	Contextual moderator (single-indicator formative; observed)	Contextual control	Accounts for variation in direct system interaction and operational authority across roles.
Frequency of Interaction with rtBRMS	Contextual moderator (single-indicator formative; observed)	Contextual control	Controls for exposure intensity, which may influence perceptions and evaluations.
Flights Handled per Shift	Contextual moderator (single-indicator formative; observed)	Contextual control	Accounts for workload volume and operational complexity differences.
Operational Area / Terminal	Contextual moderator (single-indicator formative; observed)	Contextual control	Controls for structural operational differences across terminals or zones.
Primary Passenger Type	Contextual moderator (single-indicator formative; observed)	Contextual control	Accounts for flow-direction differences that may influence stability and predictability perceptions.
Years of Experience in Gate Operations	Contextual moderator (single-indicator formative; observed)	Contextual control	Controls for professional tenure, which may shape system evaluation and performance perceptions.

Table 3.8 presents all measurement items used in the survey, together with their theoretical origins and adapted wording for this study. This table is crucial because it

demonstrates that each construct is grounded in validated scales, such as UWES for engagement, WDQ for autonomy, IWPQ for performance, and DeLone-McLean extensions for usefulness and satisfaction, while also showing how items were contextualised to the rtBRMS environment. Such item-level transparency ensures content validity, demonstrates construct coverage (e.g., multiple items per dimension for reflective variables), and allows readers to assess conceptual alignment between theory and operationalisation. Including Table 3.13 here ensures that the theoretical concepts reviewed earlier are immediately linked to their empirical indicators, strengthening interpretability of later validity tests.

Table 3-8 Study 2 Measurement Items

Items	Source	Original Questionnaire Items	Statements	Response
CSR1 (Q2_1)	Moore & Benbasat, 1991; Goodhue & Thompson, 1995; Bezerra & Gomes, 2015; Halpern & Mwesiumo, 2021	The new system is better than the one it superseded.	Compared to the traditional system, rtBRMS makes gate and door transitions easier to manage.	[1][2][3][4][5]
CSR2 (Q2_2)		The system enables me to complete tasks more quickly than before.	rtBRMS reduces the time required to prepare and execute boarding or deboarding.	[1][2][3][4][5]
CSR3 (Q2_3)		The system improves coordination with other departments.	Coordination between gate staff, security, and ground handlers runs more smoothly when rtBRMS is used.	[1][2][3][4][5]
CSR4 (Q2_4)		Overall, the system improves my job performance.	Overall operational handling performance is improved with rtBRMS compared to the traditional system.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
FSP1 (Q3_1)	Hopp & Spearman, 2011; Anagnostopoulou et al., 2024; Kingman, 1961; Little, 1961		Passenger movement feels more stable and less erratic when rtBRMS is active.	[1][2][3][4][5]
FSP2 (Q3_2)			With rtBRMS, sudden surges or drops in flow are less common.	[1][2][3][4][5]
FSP3 (Q3_3)			The boarding and deboarding process feels smoother when rtBRMS is used.	[1][2][3][4][5]
FSP4 (Q3_4)			rtBRMS helps maintain a steady pace of passenger movement.	[1][2][3][4][5]
PSP1 (Q4_1)	Körber, 2019; Lee & See, 2004; Chiou & Lee, 2023	The system behaves consistently in similar situations.	rtBRMS behaves consistently across comparable gate conditions.	[1][2][3][4][5]
PSP2 (Q4_2)		It is easy to predict what the system will do next.	I can anticipate how rtBRMS will act when passenger flows change.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
PSP3 (Q4_3)		The system state was always clear to me.	The decisions taken by rtBRMS during boarding or deboarding are predictable.	[1][2][3][4][5]
PSP4 (Q4_4)		It was easy to predict what the system would do next.	The routing and pacing actions of rtBRMS are easy to foresee in real time.	[1][2][3][4][5]
AUT1 (Q5_1)	Morgeson & Humphrey, 2006; Hackman & Oldham, 1976; Christian, Garza and Slaughter, 2011.	The job allows me to make my own decisions about how to schedule my work.	rtBRMS allows me to manage gate timing and sequencing with more control.	[1][2][3][4][5]
AUT2 (Q5_2)		The job gives me a chance to use my personal initiative or judgment in carrying out the work.	I feel able to intervene proactively when unexpected events occur.	[1][2][3][4][5]
AUT3 (Q5_3)		The job gives me considerable opportunity for independence and freedom in how I do the work.	Flow stability from rtBRMS gives me greater operational autonomy.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
JSR1 (Q6_1)	Oprea et al., 2024; Hopp & Spearman, 2011; Karasek et al., 1998	My job is hectic. My job requires working very fast.	Peak time boarding and deboarding feel less stressful with rtBRMS.	[1][2][3][4][5]
JSR2 (Q6_2)		I am not given enough time to get the job done.	I experience less time pressure at the gate when passenger flows are stabilised by rtBRMS.	[1][2][3][4][5]
JSR3 (Q6_3)		I have excessive work to do.	rtBRMS reduces my concerns about congestion near doors or aisles.	[1][2][3][4][5]
ENG1 (Q7_1)	Schaufeli et al., 2006; Schaufeli et al., 2017	At my job, I feel bursting with energy.	I feel energised when carrying out my tasks while rtBRMS is in use.	[1][2][3][4][5]
ENG2 (Q7_2)		I am enthusiastic about my work.	I am enthusiastic about performing gate-related tasks supported by rtBRMS.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
ENG3 (Q7_3)		I am immersed in my work.	I become absorbed in my work during gate operations when rtBRMS is active.	[1][2][3][4][5]
PCP1 (Q8_1)	Seddon & Kiew, 1996; DeLone & McLean, 2003	The system is useful to me in my job.	rtBRMS helps me perform my gate tasks more effectively.	[1][2][3][4][5]
PCP2 (Q8_2)		The system improves my job performance.	rtBRMS contributes to the quality of my work.	[1][2][3][4][5]
PCP3 (Q8_3)		The system enhances my effectiveness.	rtBRMS supports me in working more efficiently during turnarounds.	[1][2][3][4][5]
IWP1 (Q9_1)	Koopmans et al., 2013	I completed my work accurately.	I complete my gate tasks accurately and with attention to detail.	[1][2][3][4][5]
IWP2 (Q9_2)		I kept in mind the results that I had to achieve. I worked to the best of my ability.	I achieve the expected performance level in gate operations.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
IWP3 (Q9_3)		I managed to plan my work so that it was done on time.	I handle my workload effectively, even during demanding gate situations.	[1][2][3][4][5]
EMP1 (Q10_1)	Chatterjee, Chaudhuri and Vrontis (2022), Millmore et al., 2007; Kaur, Stoltzfus and Yellapu , 2020; Ashraf, 2020; Oprea et al., 2024.	The system increases my productivity.	With rtBRMS, I can handle more tasks within the same time frame.	[1][2][3][4][5]
EMP2 (Q10_2)		The system improves my job performance.	rtBRMS enables higher productivity during gate turnarounds.	[1][2][3][4][5]
EMP3 (Q10_3)		The system is useful to me in my job.	The use of rtBRMS improves overall efficiency in gate operations.	[1][2][3][4][5]
SS1 (Q11_1)		Overall, I am satisfied with the system.	Overall, I am satisfied with rtBRMS as a support system for gate operations.	[1][2][3][4][5]

Items	Source	Original Questionnaire Items	Statements	Response
SS2 (Q11_2)	Cammann et al., 1979	The system meets my expectations.	rtBRMS meets my expectations as a tool for managing passenger flow.	[1][2][3][4][5]
SS3 (Q11_3)		I am pleased with the system.	I would prefer to use rtBRMS rather than operate without it.	[1][2][3][4][5]

Note: The "Response" column shows the five response anchors used for every reflective item in the survey. Each item was rated on a five-point Likert scale, where [1] = strongly disagree, [2] = disagree, [3] = neither agree nor disagree, [4] = agree, and [5] = strongly agree.

3.8.4 PLS-SEM Analysis Procedures

The analysis employs partial least squares structural equation modelling (PLS-SEM) using SmartPLS 4 software, following established guidelines for model estimation, evaluation, and interpretation (Hair, Hult, Ringle and Sarstedt, 2022). PLS-SEM is selected over covariance-based SEM (CB-SEM) for several reasons: it accommodates both reflective and formative measurement models, maximizes explained variance in endogenous constructs, handles smaller sample sizes effectively, and aligns with the predictive-analytics paradigm prioritized in exploratory research (Shmueli, 2010; Hair et al., 2019).

Prior PLS-SEM research on job satisfaction and organisational commitment in technology-intensive operational contexts has demonstrated the suitability of variance-based estimation for modelling latent attitudinal outcomes alongside reflective and formative antecedents (Valaei and Rezaei, 2016), and the present model adopts the same evaluation logic adapted to the operator user-experience cascade in airport gate operations.

The analysis proceeds in two stages: (1) measurement model evaluation to assess construct validity and reliability, and (2) structural model evaluation to estimate path coefficients and assess predictive validity (Hair, Hult, Ringle and Sarstedt, 2022). This sequential approach ensures that constructs are measured validly before interpreting structural relationships, preventing spurious findings from measurement error (Fornell and Larcker, 1981).

Measurement Model Evaluation

Measurement model evaluation for reflective constructs assesses internal consistency reliability, convergent validity, and discriminant validity (Hair, Hult, Ringle and Sarstedt, 2022). Internal consistency is evaluated using composite reliability (CR > 0.70) and Cronbach's alpha ($\alpha > 0.70$), with values between 0.70 and 0.95 indicating adequate reliability (Nunnally and Bernstein, 1994). Convergent validity is assessed through average variance extracted (AVE > 0.50), indicating that constructs explain more than half the variance in their indicators (Fornell and Larcker, 1981). Discriminant validity

is evaluated using the Fornell-Larcker criterion (√AVE > inter-construct correlations) and the heterotrait-monotrait ratio (HTMT < 0.85), ensuring that constructs are empirically distinct (Henseler, Ringle and Sarstedt, 2015).

Measurement model evaluation for formative constructs assesses collinearity, indicator weights, and nomological validity (Hair, Hult, Ringle and Sarstedt, 2022). Collinearity is evaluated using variance inflation factors (VIF < 3.3), ensuring that formative indicators are not redundant (Diamantopoulos and Winklhofer, 2001). Indicator weights are assessed for statistical significance using bootstrapping with 5,000 resamples, with non-significant indicators retained if they exhibit high outer loadings (> 0.50) indicating absolute contribution (Hair, Hult, Ringle and Sarstedt, 2022). Nomological validity is assessed by examining whether the formative construct exhibits theoretically expected relationships with other constructs in the model (Diamantopoulos and Winklhofer, 2001).

Structural Model Evaluation

Structural model evaluation assesses path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive validity (Q^2) (Hair, Hult, Ringle and Sarstedt, 2022). Path coefficients represent standardized regression weights indicating the strength and direction of relationships between constructs, with significance assessed through bootstrapping (5,000 resamples, bias-corrected confidence intervals) (Efron and Tibshirani, 1993). The coefficient of determination (R^2) indicates the proportion of variance explained in endogenous constructs, with values of 0.25, 0.50, and 0.75 representing weak, moderate, and substantial explanatory power (Hair, Hult, Ringle and Sarstedt, 2022).

Effect sizes (f^2) quantify the substantive impact of predictor constructs on endogenous constructs, calculated as the change in R^2 when a predictor is removed from the model (Cohen, 1988). Values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, providing standardized measures of practical significance (Hair, Hult, Ringle and Sarstedt, 2022). Predictive validity is assessed using Stone-Geisser's Q^2 statistic,

calculated through blindfolding procedures with omission distance 7 (Geisser, 1974; Stone, 1974). Positive Q^2 values indicate that the model predicts better than the mean, with values > 0.25 indicating substantial predictive relevance (Hair, Hult, Ringle and Sarstedt, 2022).

The analysis also employs PLSpredict to assess out-of-sample predictive performance, comparing PLS-SEM predictions against linear model benchmarks (Shmueli et al., 2019). PLSpredict uses k-fold cross-validation (default k=10 in SmartPLS) to generate holdout-sample predictions, calculating root mean squared error (RMSE) and mean absolute error (MAE) for each indicator (Shmueli et al., 2019). If PLS-SEM predictions exhibit lower RMSE than linear models for all or most indicators, the model demonstrates high predictive power; if RMSE is lower for some indicators, the model demonstrates medium predictive power; if RMSE is higher for all indicators, the model demonstrates low predictive power (Shmueli et al., 2019).

3.8.5 Common Method Bias and Validity Threats

Common method bias (CMB) arises when variance in responses is attributable to measurement method rather than constructs of interest, threatening construct validity and inflating correlations (Podsakoff et al., 2003). The study addresses CMB through procedural remedies during survey design and statistical remedies during analysis (MacKenzie and Podsakoff, 2012).

Procedural Remedies

Procedural remedies include: (1) ensuring respondent anonymity to reduce evaluation apprehension and social-desirability bias, (2) separating predictor and criterion variables through survey section breaks and instructions, (3) varying response formats by using a 7-point scale for SS and 5-point scales for the other reflective and formative constructs, (4) employing balanced and neutral item wording to discourage acquiescent response sets, and (5) pilot testing to identify and eliminate ambiguous items (Podsakoff et al., 2003). These design features reduce the likelihood that CMB will systematically influence responses (MacKenzie and Podsakoff, 2012).

Statistical Remedies

Statistical remedies include: (1) Harman's single-factor test, examining whether a single factor accounts for the majority of variance in exploratory factor analysis (variance explained < 50% indicates CMB is not dominant), (2) marker variable technique, including a theoretically unrelated construct to estimate and partial out method variance, and (3) full collinearity assessment, calculating VIF for all constructs with VIF > 3.3 indicating potential CMB contamination (Kock, 2015). If multiple tests indicate CMB is not a substantial threat, the study proceeds with confidence that findings reflect substantive relationships rather than method artifacts (Podsakoff et al., 2003).

Additional Validity Threats

Additional validity threats include non-response bias, self-selection bias, and social desirability bias (Saunders, Lewis and Thornhill, 2019). Non-response bias is assessed by comparing early and late respondents on demographic characteristics and key variables, with non-significant differences indicating that non-respondents are similar to respondents (Armstrong and Overton, 1977). Self-selection bias is mitigated through random sampling and high response rates, reducing the likelihood that respondents differ systematically from non-respondents (Bryman, 2016). Social desirability bias is addressed through anonymity assurances, neutral question wording, and balanced item phrasing that avoids leading respondents toward favourable evaluations of the system (Podsakoff et al., 2003).

3.8.6 Integration with Study 1 Findings

Study 2 findings will be integrated with Study 1 results to provide a comprehensive understanding of rtBRMS effectiveness. While Study 1 establishes causal effects on operational metrics, Study 2 illuminates the operator user-experience mechanisms through which these effects occur. The integration addresses three key questions: (1) Do user-experience improvements align with operational improvements? (2) Which operator user-experience pathways are strongest predictors of performance? (3) What individual and contextual factors moderate these relationships?

The integration employs triangulation logic, where convergence between operational and user-experience evidence strengthens causal claims while divergence identifies boundary conditions or implementation challenges (Jick, 1979). For example, if Study 1 shows turnaround time improvements but Study 2 reveals low perceived usefulness, this suggests that benefits are not salient to operators, indicating need for interface redesign or training. Conversely, if both studies show positive effects, this provides strong evidence that rtBRMS delivers value through the theorized mechanisms (Shadish, Cook and Campbell, 2002).

3.9 ETHICAL CONSIDERATIONS

Ethical considerations are paramount in research involving human participants and operational data from commercial aviation environments (Saunders, Lewis and Thornhill, 2019). This study adheres to established ethical principles including respect for persons, beneficence, and justice, ensuring that research activities protect participant welfare, maintain confidentiality, and distribute benefits and burdens equitably. The research protocol has been reviewed and approved by the university ethics committee and the participating airport's data protection officer (see Appendix A), ensuring compliance with institutional requirements and regulatory frameworks including the General Data Protection Regulation (GDPR) (European Parliament, 2016).

Informed consent is obtained from all survey participants through an electronic consent form presented before survey access (Dillman, Smyth and Christian, 2014). The consent form explains the research purpose, procedures, risks, benefits, confidentiality protections, and voluntary nature of participation, ensuring that participants make informed decisions about involvement. Participants are informed that they may withdraw at any time without penalty and that their responses will be anonymized and aggregated, preventing identification of individual respondents (Saunders, Lewis and Thornhill, 2019). The consent form also provides contact information for the research team and ethics committee, enabling participants to raise concerns or request additional information (Bryman, 2016).

Confidentiality and data protection are ensured through multiple safeguards. Survey responses are collected through secure web platforms with encrypted transmission and storage, preventing unauthorized access (European Parliament, 2016). Operational data are anonymized by removing personally identifiable information and replacing flight numbers with random identifiers, ensuring that individual flights and staff cannot be identified (Saunders, Lewis and Thornhill, 2019). Data are stored on password-protected servers with access restricted to the research team, and will be retained for five years as required by institutional policy before secure deletion (Bryman, 2016). Data sharing agreements with the airport operator specify permitted uses, confidentiality requirements, and publication restrictions, ensuring that commercial interests are protected while enabling scientific dissemination (European Parliament, 2016).

Potential risks to participants are minimal, limited to the time burden of survey completion (approximately 10 minutes) and potential discomfort from reflecting on work experiences (Saunders, Lewis and Thornhill, 2019). These risks are mitigated through voluntary participation, anonymous responses, and survey design that avoids sensitive or intrusive questions (Bryman, 2016). Potential benefits include contribution to scientific knowledge, improvement of operational systems, and enhanced understanding of technology implementation in aviation contexts. While individual participants may not receive direct benefits, the research contributes to broader improvements in airport operations and work organization that may benefit the aviation workforce collectively (Saunders, Lewis and Thornhill, 2019).

The study also addresses ethical considerations specific to quasi-experimental field research, where operational interventions may affect service quality and passenger experience (Shadish, Cook and Campbell, 2002). The rtBRMS system is deployed as a pilot program with operational oversight, ensuring that any adverse effects can be detected and mitigated promptly (Kim, Barnhart and Clarke, 2017). The system is designed to improve rather than degrade operational performance, and control flights continue to operate under standard procedures that meet established safety and service standards (Schultz, 2018). The research does not involve deception, coercion, or manipulation of

participants beyond the naturally occurring variation in system deployment. These safeguards ensure that the research adheres to ethical principles while generating valid scientific evidence (Saunders, Lewis and Thornhill, 2019).

3.10 RESEARCH QUALITY AND RIGOR

Research quality across both studies is addressed through the four established validity dimensions and reliability (Shadish, Cook and Campbell, 2002; Lincoln and Guba, 1985). Internal validity is supported in Study 1 by 48-stratum stratification (gate topology × time-of-day × day type × flight type), within-stratum covariate adjustment via Type-III General Linear Models for continuous outcomes, Welch-robust contrasts under heteroscedasticity, and Firth-penalised logistic regression for the binary fast-process KPIs that handles complete separation (Firth, 1993). External validity is supported by the 48-stratum design, which captures diverse operational conditions and reveals treatment-effect heterogeneity, enabling readers to assess transferability to comparable contexts (Lincoln and Guba, 1985; Shadish, Cook and Campbell, 2002); Study 2 supplements this through random sampling of frontline operators across roles, experience, and shifts, with moderation analyses identifying boundary conditions (Bryman, 2016).

Construct validity is supported in Study 1 by objective operational metrics extracted from automated systems (Kim, Barnhart and Clarke, 2017) and in Study 2 by validated psychometric scales with established reliability (Hair, Hult, Ringle and Sarstedt, 2022); common method bias is addressed through procedural separation of predictor and criterion measures, anonymity, varied response anchors, balanced and neutral item wording, and statistical remedies including Harman's single-factor test and full collinearity VIF assessment (Kock, 2015). Statistical conclusion validity is supported by sample sizes adequate for detecting practically meaningful effects (Cohen, 1988), tests appropriate for unbalanced and heteroscedastic data (Welch, 1938; Nelder and Wedderburn, 1972), 5,000-resample bootstrapping in PLS-SEM (Efron and Tibshirani, 1993), and predictive validity assessment via cross-validation (Shmueli et al., 2019); effect sizes are reported with confidence intervals throughout (Cumming, 2014).

Reliability is supported by automated extraction of operational data, minimising human error (Kim, Barnhart and Clarke, 2017), and by multi-item scales with Cronbach's $\alpha > 0.70$ (Nunnally and Bernstein, 1994); both studies document procedures to enable replication (Saunders, Lewis and Thornhill, 2019).

3.11 INTEGRATION OF DUAL-STUDY DESIGN

The dual-study design integrates complementary methodological approaches to provide comprehensive understanding of how rtBRMS influences both operational performance and operator behaviour (Creswell and Creswell, 2018). While each study addresses a distinct facet of the research objectives using appropriate methods, their integration enables triangulation of findings and synthesis of system-level and human-level perspectives (Bryman, 2016). This integration reflects the socio-technical nature of airport operations, where technology effectiveness depends on both technical performance and human acceptance (Schultz, 2018).

The integration occurs at three levels: conceptual, empirical, and interpretive (Saunders, Lewis and Thornhill, 2019). At the conceptual level, both studies are grounded in the same theoretical framework that positions rtBRMS as a socio-technical intervention influencing operational processes and operator user-experience perceptions (Venkatesh, Brown and Bala, 2013). Study 1 examines the operational mechanisms through which rtBRMS stabilizes passenger flow and reduces turnaround variability, while Study 2 examines the operator user-experience mechanisms through which operators perceive and respond to this stabilization (Hair, Hult, Ringle and Sarstedt, 2022). These mechanisms are conceptually linked: operational stabilization creates the conditions for enhanced predictability, which in turn influences usefulness perceptions, engagement, and performance (Endsley, 2017).

At the empirical level, both studies are conducted at the same operational site during the same calendar year. Study 1 captures flight-level outcomes during a six-month observation window in late 2025; Study 2 collects operator perceptions over a three-week window in March 2026, approximately three months after the close of Study 1, allowing

operator perceptions to stabilise around routine rtBRMS use rather than novelty reactions. Study 1 provides objective evidence of operational effects, quantifying changes in turnaround time, milestone achievement, and variance reduction (Kim, Barnhart and Clarke, 2017). Study 2 provides subjective evidence of operator user-experience effects, quantifying changes in perceived predictability, usefulness, engagement, and self-reported performance (Hair, Hult, Ringle and Sarstedt, 2022). The convergence or divergence of objective and subjective performance measures provides insights into the alignment between system capabilities and operator perceptions (Venkatesh, Brown and Bala, 2013).

At the interpretive level, findings from both studies are synthesized to develop integrated explanations of rtBRMS effectiveness (Bryman, 2016). If Study 1 demonstrates operational improvements and Study 2 demonstrates positive operator user-experience responses, the synthesis supports the conclusion that rtBRMS is effective at both system and human levels (Creswell and Creswell, 2018). If Study 1 demonstrates operational improvements but Study 2 reveals negative operator user-experience responses, the synthesis identifies implementation challenges that may undermine long-term sustainability (Schultz, 2018). If Study 1 demonstrates minimal operational effects but Study 2 reveals positive operator user-experience responses, the synthesis suggests that perceived benefits may exceed objective benefits, raising questions about expectation management (Venkatesh, Brown and Bala, 2013). These interpretive possibilities illustrate how the dual-study design enables nuanced understanding that neither study could provide alone (Saunders, Lewis and Thornhill, 2019).

3.12 ANTICIPATED DESIGN CONSTRAINTS AND DELIMITATIONS

Three limitations are explicitly acknowledged. First, the quasi-experimental design cannot match the internal validity of randomised controlled trials. Confounding from observable operational characteristics is addressed through the fully-crossed 48-stratum design (4 gate topologies × 3 temporal periods × 2 day types × 2 flight types) and through within-stratum covariate adjustment via Type-III General Linear Models for the continuous outcomes and Firth-penalised logistic regression for the binary fast-process KPIs (Firth, 1993), but residual confounding from unobserved factors such as seasonality, crew

rotation, or parallel process improvements cannot be ruled out (Shadish, Cook and Campbell, 2002). Random assignment was infeasible as it would have disrupted live operations and compromised ecological validity (Kim, Barnhart and Clarke, 2017). Random assignment was infeasible as it would have disrupted live operations and compromised ecological validity (Kim, Barnhart and Clarke, 2017). Second, the single-site design at Mashhad International Airport restricts statistical generalisation; transferability is bounded through the 48-stratum description rather than claimed for all airports, and multi-site replication is left to future research (Schultz, 2018). Third, the cross-sectional time horizon prevents analysis of learning effects, adaptation, and long-term sustainability, and limits causal ordering among latent constructs in Study 2; longitudinal extensions are appropriate for future work (Hair, Hult, Ringle and Sarstedt, 2022; Venkatesh, Brown and Bala, 2013).

Two delimitations are intentional. The study focuses on short-haul operations at Mashhad operating under A-CDM protocols, excluding long-haul, non-A-CDM, and other regional contexts (EUROCONTROL, 2017). It examines rtBRMS effects on turnaround performance and operator behaviour, excluding financial, customer-experience, and environmental outcomes (Saunders, Lewis and Thornhill, 2019). These boundaries make the empirical investigation tractable while leaving identifiable directions for subsequent research.

Two further limitations specific to integration and measurement deserve note. First, Study 2 was administered three months after the Study 1 observation window. This sequencing was deliberate: by March 2026 staff had been working with rtBRMS for an extended period and were reporting stable, experience-based perceptions rather than novelty reactions; the trade-off is that user-experience data describe the operational regime as a whole rather than the specific Study 1 week. Second, Study 1 operates at the flight level while Study 2 operates at the operator level; the integration assumes that flight-level variance reduction translates into individual-level perception, an assumption not directly tested here. Multilevel designs in future research could link the two levels explicitly. Self-report measurement in Study 2 is mitigated through anonymity, neutral item wording,

formative-composite specification where appropriate, Harman's single-factor test, and full-collinearity VIF assessment; non-response (32%) is bounded through wave analysis comparing early and late respondents on construct means (Armstrong and Overton, 1977; Podsakoff et al., 2003; Kock, 2015).

3.13 CHAPTER SUMMARY

This chapter set out the methodological architecture grounding the empirical investigation. The study adopts a post-positivist position that treats operational processes as objectively measurable and operator user-experience constructs as latent variables manifest in observable response patterns (Bryman, 2016; Hair, Hult, Ringle and Sarstedt, 2022). Within an exclusively quantitative, multi-method design, Study 1 estimates the causal effect of rtBRMS on Gate Occupation Time, boarding-window duration, deboarding-window duration, and passenger throughput across 171 flights at Mashhad International Airport, using a fully-crossed 48-stratum field design (4 gate topologies × 3 temporal periods × 2 day types × 2 flight types) with within-stratum covariate adjustment via Type-III General Linear Models for the continuous outcomes and Firth-penalised logistic regression for the binary fast-process KPIs (Shadish, Cook and Campbell, 2002; Firth, 1993). Study 2 estimates the operator user-experience pathways from perceived predictability and autonomy through engagement to performance and satisfaction across 224 frontline operators using PLS-SEM with validated scales (Schaufeli and Bakker, 2004; Venkatesh and Davis, 2000; Koopmans et al., 2013; Hair et al., 2022). Both studies are deductive within their own scope and integrated through theory-driven synthesis at the inference stage in Chapter 6. Each design decision is traceable to a specific research objective; limitations of quasi-experimental, cross-sectional, single-site research are acknowledged in Section 3.12. Chapters 4 and 5 present the empirical findings; Chapter 6 integrates them.

4. DATA ANALYSIS AND MEASUREMENT VALIDATION

4.1 OVERVIEW OF THE CHAPTER

This chapter documents the methodological implementation of the dual-study research design specified in Chapter 3. Where Chapter 3 set out the philosophical position, design rationale, sampling logic, and analytical strategy, this chapter reports how those decisions were operationalised in practice: how Study 1's data were acquired, reconciled, and analysed under the 48-stratum field design at Mashhad International Airport; how Study 2's instrument was developed, translated, and administered to 224 frontline operators; and how the two evidence streams were prepared for integration in Chapter 5. The chapter is organised as two phases that mirror the chronological development of the programme.

Section 4.2 documents the Study 1 implementation: the field-experiment site and observation window, the sampling and eligibility rules, the dependent and control variables, and the analytical strategy. Section 4.3 documents the Study 2 implementation: pre-test and pilot, common-method-variance and non-response-bias safeguards, data handling and governance, the measurement-first PLS-SEM evaluation framework, the structural model estimation procedures, the choice of SmartPLS, the forward-backward translation procedure, and the integration logic that links Study 1 and Study 2 evidence. Section 4.4 closes the chapter with a summary of the implementation choices.

4.2 STUDY 1: DESIGN, MEASURES, AND ANALYTICAL APPROACH

Study 1 was conducted as a 48-stratum field experiment at Mashhad International Airport (MHD), with strata formed by the factorial combination of gate architecture (four types, from single-access to shared-access multi-door configurations), temporal band (peak, off-peak, transitional), and flight type (domestic, international, mixed). Sampling, eligibility criteria, control variables (passenger load, aircraft type, crew composition, weather band), and the operationalisation of the dependent measures, namely Gate Occupation Time, boarding window, deboarding window, passengers per minute, and binary KPI attainment, follow the protocol established in Sections 3.7.1 and 3.7.2. Event-

level logs from the rtBRMS infrastructure were aggregated to flight-level analytics using the data-handling rules specified in Section 3.7.5, and the analytical sample reported in Section 5.2 reflects the application of the analytical plan as specified in advance of data analysis, without modification.

The analytical strategy combines Welch t-tests for unadjusted contrasts under unequal variances, Type III General Linear Models for covariate-adjusted effect estimation under the unbalanced 48-cell design, and Firth-penalised logistic regression for the binary fast-process KPIs, applied as specified in Section 3.7.6. Robustness checks include heteroscedasticity-consistent standard errors for the continuous outcomes, comparison of unadjusted and covariate-adjusted estimates to identify covariate-driven shifts, and Variance Inflation Factor screening for multicollinearity. Ethical approval for the field study, anonymisation of operational records, and data-handling standards follow Sections 3.7.5 and 3.9, and no additional ethical issues arose during fieldwork. The descriptive baseline and inferential tests of the Study 1 hypotheses are reported in Chapter 5 (Section 5.2).

Table 4-1 Summary of Analytical Methods by Outcome Type

Outcome Variable	**Measurement Scale**	**Unadjusted Method**	**Adjusted Method**	**Effect Size Metric**
Gate Occupation Time	Continuous (minutes)	Welch's t-test	GLM with Type III SS	Cohen's *d*, Partial η^2
Boarding Window	Continuous (minutes)	Welch's t-test	GLM with Type III SS	Cohen's *d*, Partial η^2
Deboarding Window	Continuous (minutes)	Welch's t-test	GLM with Type III SS	Cohen's *d*, Partial η^2
$\text{Throughput}_{\text{board}}$	Continuous (pax/min)	Welch's t-test	GLM with Type III SS	Cohen's *d*, Partial η^2

Outcome Variable	Measurement Scale	Unadjusted Method	Adjusted Method	Effect Size Metric
$\text{Throughput}_{\text{deboard}}$	Continuous (pax/min)	Welch's t-test	GLM with Type III SS	Cohen's *d*, Partial η^2
High-Performance Boarding	Binary (≤13 min)	—	Binary logistic regression with covariates	Odds ratio (95% CI), classification accuracy
High-Performance Deboarding	Binary (≤11 min)	—	Firth-penalised binary logistic regression (separation)	Odds ratio (95% CI), classification accuracy

4.3 STUDY 2: SAMPLING, INSTRUMENT, AND CONSTRUCT OPERATIONALISATION

Study 2 surveyed frontline operators (gate agents, gate managers, ramp coordinators, dispatchers, supervisors, security personnel, ground-handling staff, and safety personnel) involved in rtBRMS-supported operations at Mashhad International Airport, using the bilingual English–Farsi instrument finalised in the pilot phase. Recruitment channels, eligibility criteria, language allocation, and informed-consent procedures follow the protocol in Section 3.8.2; no protocol amendments were made after pilot completion. No incentives were offered for participation; consistent with the institutional ethics approval, participation was entirely voluntary. The achieved sample of 224 valid responses (described in detail in Section 5.3.1) meets the a-priori power and PLS-SEM stability thresholds specified in Chapter 3 (Sampling and Data Collection).

Construct operationalisation, item sources, scaling, and the formative-reflective designations (Flow Stability Perception [FSP, formative], Perceived System Predictability [PSP], Perceived Autonomy [AUT], Job Stress Reduction [JSR], Comparative Superiority of rtBRMS [CSR, formative], Perceived Performance Contribution [PPC], Work

Engagement [ENG], Individual Work Performance [IWP], Employee Productivity [EMP], and System Satisfaction [SS]) follow the construct-specification map in Section 3.8.3. All items were drawn from established scales and adapted to the gate-operations context using the wording, reverse-coding, and anchor conventions documented in Chapter 3, with no post-hoc item modifications introduced into the analytical pipeline.

Table 4-2 Summary of Survey Development and Validation Process

Stage	Participants	Purpose	Key Activities
Pre-Test	2 academics + 2 practitioners	Content validity and clarity	Expert review of item wording, construct boundaries, and conceptual distinctions; verification of theoretical alignment
Pilot Test	34 operational participants	Reliability and instrument functionality	Evaluation of response stability, completion time, platform usability; identification of comprehension barriers; preliminary reliability analysis
Final Data Collection	224 airport operational staff	Empirical testing of research hypotheses	Full survey administration across roles, experience levels, and shift patterns; comprehensive measurement and structural model testing

Table 4.2 summarises the structured, multi-stage procedure used to develop and validate the survey instrument, demonstrating that the measurement architecture rests on rigorous methodological foundations. The process begins with a pre-test involving academic experts and experienced practitioners, ensuring content validity by verifying that

item wording, construct boundaries, and conceptual distinctions (e.g., FSP vs. PSP; AUT vs. JSR) were clear and theoretically aligned.

4.3.1 Pre-Test and Pilot

The process begins with a pre-test involving academic experts and experienced practitioners, ensuring content validity by verifying that item wording, construct boundaries, and conceptual distinctions (e.g., FSP vs. PSP; AUT vs. JSR) were clear and theoretically aligned. Second, a pilot with 34 participants tested completion time, response variability, and platform stability; pilot cases were excluded from the main PLS-SEM analysis to protect inferential integrity. Pilot completion time averaged approximately 10 minutes, well within acceptable limits for operational staff during shift breaks. Response-variability analysis confirmed that all items exhibited adequate variance (no floor or ceiling effects, all standard deviations > 0.6 on the 5-point scales), and platform-stability testing verified that the online survey system functioned reliably across the devices and browsers used at the study airport.

4.3.2 Data Handling, Governance, and Security

The platform was configured for anonymous capture (no IP storage; no direct identifiers). Records include only coarse-grained role/tenure/exposure variables. Data were exported to an institutional repository with two tiers, a read-only raw dataset and a working analysis dataset, with all transformations logged for auditability. Access to raw data was restricted to the PI/supervisors; working files were version-controlled and backed up.

In line with institutional policy, anonymised data are retained for at least five years; analytic code and de-identified artefacts are archived in the institutional repository to support post-submission verification. The data-management approach satisfies the institutional research-data policy and the principles of research transparency and reproducibility set out in the University of Worcester Policy for the Effective Management of Research Data.

4.3.3 Measurement-First Evaluation (PLS-SEM)

Building on the PLS-SEM evaluation framework established in Chapter 3 (Section 3.8.4), this section specifies the exact thresholds and diagnostic criteria applied to the data collected in this study. The analysis follows a measurement-first discipline because PLS-SEM requires that all constructs demonstrate satisfactory psychometric quality before any structural relationships can be meaningfully interpreted. The eight reflective constructs in the model (PSP, AUT, JSR, ENG, PPC, IWP, EMP, SS) are first evaluated through a comprehensive reliability and validity assessment:

- **Cronbach's α and Composite Reliability (CR):** Ensure internal consistency across indicators (thresholds: $\alpha \geq 0.70$, $CR \geq 0.70$) (Nunnally and Bernstein, 1994).

- **Average Variance Extracted (AVE):** Confirms that each construct explains more than half of the variance in its items (threshold: $AVE \geq 0.50$) (Fornell and Larcker, 1981).

- **Indicator Loadings:** Establish that items meaningfully reflect the underlying latent variable (threshold: $\lambda \geq 0.70$, though 0.60–0.70 acceptable for exploratory research).

- **HTMT Ratios:** Verify discriminant validity among closely related constructs (threshold: HTMT < 0.85 for conceptually distinct constructs, <0.90 for conceptually similar constructs) (Henseler, Ringle and Sarstedt, 2015).

- **VIF Diagnostics:** Assess multicollinearity to ensure that indicators do not inflate structural estimates (threshold: VIF < 5, ideally < 3).

These checks ensure that each reflective construct behaves as a coherent, empirically stable operator user-experience entity prior to inclusion in the predictive model. For FSP and CSR, which are modelled as first-order formative composites, the evaluation must follow formative-measurement logic because their indicators represent distinct, non-interchangeable dimensions of the construct rather than interchangeable

reflections of a single latent perception (Diamantopoulos and Winklhofer, 2001; Hair, Hult, Ringle and Sarstedt, 2022). Accordingly, each formative block is assessed through:
Accordingly, the formative block is assessed through:

- **Outer Weights:** Outer Weights: Quantify the relative contribution of each dimension to the composite; significance of weights via 5,000-resample bootstrapping indicates that the indicator contributes meaningfully (Hair et al., 2022).

- **Outer Loadings:** Where outer weights are non-significant, outer loadings ≥ 0.50 justify retention for content coverage, since formative indicators are theoretically defining facets and cannot be dropped without altering the construct's domain (Coltman et al., 2008).

- **Formative VIF Values**: Test whether indicators inflate one another via multicollinearity (threshold: VIF < 5).
- **Redundancy Analysis:** Comparing the formative HOC with a global, reflective FSP item (target $r \geq 0.708$) to verify that the composite adequately captures the intended conceptual space.

Only once both reflective and formative constructs demonstrate acceptable reliability, convergent and discriminant validity, and absence of problematic collinearity does the analysis proceed to evaluating the structural paths. This staged "measurement-first, structure-second" approach ensures that observed relationships among constructs reflect theoretical mechanisms rather than artefacts of measurement error, in line with the standard PLS-SEM evaluation protocol (Hair et al., 2022).

4.3.4 Structural Model Estimation and Reporting

Building on the structural estimation approach outlined in Section 3.8.4, structural relationships are estimated using PLS-SEM with bootstrapping at 5,000 resamples to obtain stable standard errors and robust significance estimates without distributional assumptions, which is essential for variance-based SEM with multiple intervening

constructs, formative constructs, and moderation terms (Hair et al., 2022). Results are reported as standardised path coefficients (β) with 95% bias-corrected confidence intervals and p-values, accompanied by f^2 local effect sizes computed as $f^2 = (R^2\text{included} - R^2\text{excluded}) / (1 - R^2\text{included})$ and benchmarked against Cohen's (1988) thresholds (0.02 small, 0.15 medium, 0.35 large). R^2 values are reported for all endogenous constructs (PSP, PPC, ENG, IWP, EMP, SS), and Q^2 values from blindfolding and PLSpredict provide evidence of out-of-sample predictive relevance per Shmueli et al. (2019).

Robustness checks include re-estimation of the second-order formative specification of FSP under both two-stage and repeated-indicator approaches, and re-estimation of structural paths across role, exposure frequency, and workload subgroups where size permits, to verify mechanism stability across operational conditions. Predictive adequacy is assessed via PLS predict by comparing PLS-SEM RMSE and MAE against a linear-model benchmark (Shmueli et al., 2019); the model is judged predictively relevant only when prediction errors are lower than the benchmark for the majority of indicators. Boundary conditions are probed through eight moderation hypotheses (S2-H10–S2-H17) testing whether passenger type, interaction frequency, level of responsibility, years of experience, operational area, role, and flights per shift moderate specific structural pathways, using the two-stage PLS approach with mean-centred product terms and bootstrap inference (Hair et al., 2022; Henseler, Ringle and Sarstedt, 2015). Where a moderation effect reaches statistical significance, the conditional effects are reported in the corresponding row of Table 5.23.

4.3.5 Analytical Tool Selection: SmartPLS Alignment with Study Design

SmartPLS 4 is selected for Study 2 because the model's structural and statistical properties make it the most efficient and well-validated platform for this design. The model links eight reflective latent variables (PSP, AUT, JSR, ENG, PPC, IWP, EMP, SS) and two formative composites (FSP, CSR) through 17 direct effects (S2-H1 - S2-H9b) and 8 moderation hypotheses (S2-H10 to S2-H17), combining reflective measurement of psychological states with formative measurement of user-experience composites. Covariance-based SEM is unsuitable on three counts: it requires multivariate normality

that operational survey data do not satisfy, it does not natively accommodate formative composites without identification constraints, and it requires substantially larger samples for convergence at this complexity (Hair et al., 2022; Rezaei, 2015). PLS-SEM is variance-based, distribution-free, designed for prediction and theory-extension, and produces stable estimates at the achieved N = 224, well above the heuristic minimum of ten times the maximum number of arrows pointing at any single construct (which is 40 for this model; Hair et al., 2022).

SmartPLS also delivers all analytical operations the design requires: 5,000-resample bootstrapping with bias-corrected confidence intervals (Efron and Tibshirani, 1993; Hair et al., 2022), Q^2 and PLSpredict for predictive validity (Shmueli et al., 2019), full-collinearity VIF for common-method-bias diagnostics (Kock, 2015), Fornell-Larcker and HTMT for discriminant validity (Henseler et al., 2015), and integrated two-stage moderation with simple-slope decomposition. This combination of variance-based estimation, formative-construct accommodation, sample-size efficiency, predictive validation, and moderation tooling makes SmartPLS the only platform that simultaneously satisfies the theoretical, structural, and statistical demands of the rtBRMS model under field conditions.

4.3.6 Forward–Backward Translation of the Survey Instrument

Because the research was conducted in a multilingual operational environment with varying English proficiency among frontline staff, the survey instrument underwent a rigorous forward-backward translation following Brislin's (1970, 1986) model, which is widely adopted in cross-cultural instrument adaptation (Beaton et al., 2000; Wild et al., 2005). The original English instrument was independently translated into the target language by two professional translators, both native speakers fluent in English with domain knowledge in organisational behaviour and operations management to ensure accurate rendering of technical terminology (flow stability, autonomy, strain, engagement). A bilingual expert panel (the principal investigator, one academic supervisor, one senior airport operational manager) reconciled the two forward translations into a single harmonised version preserving semantic meaning and conceptual intent.

The harmonised version was then independently back-translated into English by a third translator who had not seen the original, providing a blind validity check. The expert panel compared the back-translation against the original English instrument for conceptual, semantic, and idiomatic equivalence; discrepancies prompted iterative revision of the forward translation until satisfactory alignment was achieved. The finalised target-language instrument was then reviewed via cognitive interviews with five bilingual operational staff covering different roles (gate agents, supervisors, coordinators) and experience levels, who completed the survey while thinking aloud. These interviews showed that abstract terms such as "predictability" and "autonomy" required contextual anchoring (for example, "predictability" was anchored to "predictability of passenger flow patterns" to distinguish it from schedule predictability or equipment reliability); minor wording adjustments were made without altering construct definitions. The instrument was then pilot-tested with 34 operational staff in the target language (the pilot-test stage reported in Table 4.2), and all constructs achieved acceptable internal consistency ($\alpha \geq 0.70$) with no problematic floor or ceiling effects, confirming that translation preserved the original measurement properties. All stages were documented in a translation audit trail (original English, both forward translations, harmonised version, back-translation, expert-panel notes, cognitive-interview transcripts, pilot results) per Beaton et al. (2000) and Wild et al. (2005); the complete bilingual instrument is reproduced side-by-side in Appendix H. The instrument was approved by the institutional ethics committee and respondents could complete it in either language to maximise inclusivity and minimise language-related measurement error.

4.3.7 Integration: One Evidence Arc from Operational to User-Experience

The two-study design is not a convenience; it is an architectural necessity. Study 1 establishes that rtBRMS objectively reduces variance in passenger arrival patterns, producing smoother, more predictable flow conditions at the operational level. Study 2 tests whether frontline staff perceive this stabilisation and whether that perception translates into improved operator user-experience resources, engagement, and performance outcomes.

The integration logic follows a single, coherent evidence arc: operational variance reduction (Study 1) → perceived flow stability (Study 2) → human-factor resources (Study 2) → engagement and performance (Study 2). This arc is not merely correlational; it is mechanistic. The variance-reduction mechanism demonstrated in Study 1 provides the causal foundation for the user-experience and behavioural relationships tested in Study 2.

Operational-to-User-Experience Bridge

The bridge between studies is FSP, which operationalises employees' subjective interpretation of the stabilised flow conditions generated by rtBRMS. FSP is not a proxy for objective variance; it is the user-experience counterpart of the variance-reduction mechanism. This distinction is critical: even if rtBRMS objectively reduces variance, its human-factor benefits depend on whether staff recognise and internalise that stabilisation. By measuring FSP as a formative composite capturing multiple dimensions of perceived stability (reduced burstiness, smoother pacing, fewer oscillations), Study 2 tests whether the operational mechanism identified in Study 1 is operator user-experiencely salient to frontline workers. If FSP predicts PSP, AUT, and JSR, it confirms that the variance-reduction mechanism is not merely a statistical artefact but a lived experience that shapes employees' cognitive and motivational states.

Complementary Evidence, Not Redundant Replication

The two studies are complementary, not redundant. Study 1 provides causal evidence of the variance-reduction mechanism using objective operational data and a quasi-experimental design. Study 2 provides convergent evidence of the user-experience and behavioural consequences of that mechanism using self-reported survey data and structural equation modelling.

Neither study alone would be sufficient. Study 1 without Study 2 would demonstrate that rtBRMS reduces variance but would not explain how that reduction affects human factors. Study 2 without Study 1 would demonstrate that perceived stability predicts engagement and performance but would not establish that rtBRMS actually

produces that stability. Together, the two studies form a complete evidence chain from operational intervention to human-factor outcomes.

Triangulation and Robustness

The integration also provides methodological triangulation. Study 1 uses objective, time-stamped operational data analysed through statistical hypothesis testing and generalised linear modelling. Study 2 uses subjective, cross-sectional survey data analysed through variance-based structural equation modelling. The convergence of findings across these two methodologically distinct approaches strengthens confidence in the overall conclusion: rtBRMS stabilises passenger flows, frontline staff perceive that stabilisation, and that perception enhances operator user-experience resources, engagement, and performance.

This triangulation is particularly important in applied research, where single-method studies are vulnerable to method-specific biases and alternative explanations. By demonstrating the rtBRMS mechanism through both operational and user-experience lenses, the research provides robust, multi-method evidence that the system delivers its intended human-factor benefits.

Practical Implications of Integration

From a practical standpoint, the integrated evidence arc informs deployment, training, and human-machine interface design. Knowing that rtBRMS reduces variance (Study 1) tells system designers that the algorithm works. Knowing that staff perceive that stabilisation and that it improves their resources and performance (Study 2) tells operational managers how to communicate the system's benefits, how to train staff to recognise and leverage stabilised flow conditions, and how to design interfaces that make flow stability visible and actionable.

The integration thus transforms the research from a purely academic exercise into a decision-support framework for socio-technical system implementation. It provides evidence not only that rtBRMS works but also why it works and how its benefits can be maximised through human-centred design and operational practice.

4.4 CHAPTER SUMMARY

Chapter 4 documented the implementation of the dual-study research design specified in Chapter 3. Study 1 was conducted as a 48-stratum quasi-experimental field study at Mashhad International Airport, with event-level rtBRMS logs aggregated to flight-level analytics and analysed via Welch t-tests for unadjusted contrasts, Type III General Linear Models for covariate-adjusted effects and moderation tests, and Firth-penalised logistic regression for the binary fast-process KPIs. Study 2 was conducted as a cross-sectional anonymous survey of 224 frontline operators, with the bilingual English–Farsi instrument developed through pre-test, cognitive interviews, and pilot testing; procedural and statistical safeguards against common-method variance and non-response bias; a measurement-first PLS-SEM evaluation sequence covering eight reflective and two formative constructs; and 5,000-resample bootstrapping for path significance and indirect-effect testing. The two studies are complementary rather than redundant: Study 1 supplies causal evidence that rtBRMS reduces process-window variance and improves throughput under authentic heterogeneity, while Study 2 supplies convergent evidence that frontline staff perceive that stabilisation and that the perception propagates through predictability, autonomy, and stress-reduction pathways to engagement, performance, productivity, and satisfaction. Limitations (Section 3.12) reflect deliberate trade-offs between ecological validity and laboratory control, contextual depth at a single site and breadth across many, and cross-sectional measurement against longitudinal feasibility. Chapter 5 reports the empirical findings from both studies and integrates them into a coherent account of how rtBRMS reshapes both the cadence of gate operations and the experience of the people who manage them.

5. FINDINGS OF THE STUDY

5.1 OVERVIEW OF THE CHAPTER

This chapter reports the empirical findings of the research programme in the sequence in which the evidence was produced. The presentation follows the two-phase logic specified in the methodology. Study 1 provides a field-experimental account of the operational performance changes associated with the deployment of the real-time boarding route management system (rtBRMS) under live heterogeneity. Study 2 then reports how frontline personnel experienced and translated that operational change into self-reported predictability, engagement, performance, and satisfaction. The two studies are reported separately so that each evidential stream stands on its own analytical merit, with synthesis and interpretation reserved for the discussion that follows in Chapter 6.

The chapter is organised as follows. Section 5.2 reports the Study 1 results: the preliminary descriptive analysis and diagnostic checks, the hypothesis tests for S1-H1 through S1-H6b, and the robustness analysis that confirms the stability of the field-experimental inferences. The Study 2 results, contained in Part 2 of this chapter (*ch5-findings-2.html*), follow the same descriptive logic: the sample profile (Section 5.3.1), the measurement-model assessment (Section 5.3.2), the structural-model estimation (Section 5.3.3), decomposition of total effects (Section 5.3.4), and the predictive-validity indices (Section 5.3.5). Section 5.4 in Part 2 consolidates the hypothesis decisions across both studies, and Section 5.5 closes the chapter with a brief summary of the evidence base before the reader transitions into Chapter 6.

The statistical conventions used throughout the chapter follow Section 3.7.6 of the methodology. Hypothesis decisions are reported at $p < .05$ with the sign consistent with the directional prediction. Effect sizes are interpreted using Cohen's (1988) thresholds. PLS-SEM significance is established through 5,000 bootstrap resamples with bias-corrected and accelerated confidence intervals. Tables use standardised column headings whose meanings are defined once, in Section 5.3.2.1, and apply consistently to every subsequent table in the chapter.

5.2 RESULTS – STUDY 1 (Field Experiment, n = 171 flights)

Study 1 was conducted under the 48-stratum design described in Section 3.7, with 171 flights distributed across two treatment conditions: Legacy operations (n = 74) and rtBRMS-managed operations (n = 97). The analysis proceeded in two stages. The preliminary stage consolidated descriptive statistics and diagnostic checks across the multiple models so that individual hypothesis sections need not repeat them; the hypothesis-testing stage then estimated covariate-adjusted effects, standardised magnitudes, and planned contrasts aligned with hypotheses S1-H1 through S1-H6b. The substantive interpretation of the results — what they imply for queueing theory, for the Theory of Constraints, and for the prior boarding-optimisation literature — is reserved for Chapter 6 (Discussion).

5.2.1 Preliminary Analysis and Diagnostic Checks

Summary metrics for all continuous outcomes (Gate Occupation Time, boarding window, deboarding window, and the two throughput measures) showed the directional differences anticipated by the design, with rtBRMS-managed flights consistently producing lower time-based measures and higher flow-rate measures than Legacy flights. Distributions were unimodal with moderate dispersion, and visual inspection of group distributions revealed no patterns that would compromise linear modelling.

Levene's test confirmed unequal variances for several outcomes, motivating the use of Welch-robust contrasts for unadjusted comparisons. For the multivariate models, regression diagnostics - residual-fit plots, leverage and Cook's distance for influence, and Variance Inflation Factors for multicollinearity - returned values within accepted thresholds, with all VIF values below 5.0 across all GLMs. The binary-outcome model for the FastDeboard threshold (≤ 11 minutes) exhibited complete separation, with the rtBRMS treatment indicator perfectly classifying a subset of cases. Standard maximum likelihood was therefore replaced by Firth's penalised maximum likelihood (Firth, 1993), which produced finite, bias-reduced odds ratios and remained stable under bootstrap resampling. The full diagnostic record is consolidated within Section 5.2.3 below; the individual hypothesis sub-sections that follow do not repeat the diagnostic narrative.

5.2.2 Hypothesis Tests

The hypothesis-testing analysis proceeded along two complementary axes. Welch-robust t-tests provided unadjusted contrasts for each continuous outcome, and Type-III General Linear Models with the four operational covariates (Passenger_Count, Flights_per_Gate_per_Day, Shared_Access_Points, Self_Checkin_Used) provided covariate-adjusted estimates with EMMEANS Bonferroni contrasts. The binary outcomes were modelled through standard and Firth-penalised logistic regression with the same covariate set augmented by Gate_Type, Time_of_Day, Day_Type, and Flight_Type. Table 5.1 sets out the thematic findings; Table 5.2 reports the consolidated statistical synopsis; and Tables 5.3 - 5.8 provide the hypothesis-specific GLM and logistic-regression output.

Table 5-1 Hypotheses and Key Findings

Theme	Hypotheses	Key Result
GOT reduction	S1-H1	rtBRMS reduces Gate Occupation Time by approximately 12–13 minutes
Window compression	S1-H2a, S1-H2b	Boarding windows compressed by 15.8%; deboarding windows by 8.2%
Throughput uplift	S1-H3	Boarding and deboarding throughput each rise by approximately 1.6–1.7 passengers per minute
Architectural moderation	S1-H4	rtBRMS effects amplified at shared-access multi-door gates (Types 3–4)
Load and temporal robustness	S1-H5	Consistent 12–14 minute GOT savings across all load quartiles and temporal bands
Fast-process thresholds	S1-H6a, S1-H6b	Higher probability of meeting FastBoard (≤13 min) and FastDeboard (≤11 min) targets

Table 5-2 Hypotheses Statistical Summary

Hypothesis	Type of Data & Measures	DV(s)	IV(s) & Covariates	Analysis & Model Spec	Statistical Findings	Effect Sizes & Fit	EMMEANS / Contrasts	Implications & Decision
S1-H1 – rtBRMS main effect on GOT	Flight-level (171 flights), event-derived. Measure: GOT_min (min).	GOT_min	IV:rtBRMS_Enabled (0/1). Covariates: Passenger_Count; Flights_per_Gate_per_Day; Shared_Access_Points; Self_Checkin_Used.	Independent t-test; GLM UNIANOVA (Type III SS); EMMEANS (Bonferroni).	Means: Legacy 57.74 vs rtBRMS 44.86 → Δ=12.888 min; $t(169)=28.310$, $p<.001$; Welch $t(115.803)=26.701$, $p<.001$; 95% CI [11.989, 13.786].	Cohen's d=4.370; GLM: $F(1,165)=1134.346$, $p<.001$; partial $\eta^2=.873$; $R^2=.917$ (Adj .914).	Legacy 57.413 vs rtBRMS 45.108; Δ=12.305; $p<.001$.	rtBRMS reduces GOT by ≈12–13 min on a covariate-adjusted basis (Cohen's d = 4.37; partial η^2 = .87). **Supported.**
S1-H2 – Window efficiency	Flight-level. Measures: Deboard_Window_min; Board_Window_min (min).	Deboard_Window_min; Board_Window_min	IV: rtBRMS_Enabled. Covariates (GLM): Passenger_Count; Shared_Access_Points.	t-tests; GLM with covariates; Bonferroni pairwise.	Deboard: 24.19 vs 22.21 → Δ=1.98; $t(169)=11.879$, $p<.001$; 95% CI [1.65, 2.31]. Board: 25.71 vs 21.66 → Δ=4.05; $t(169)=16.840$, $p<.001$; 95% CI [3.58, 4.53].	d=1.83 (Deboard); d=2.60 (Board). GLM: $F(1,167)=312.62$ ($\eta^2=.652$) Deboard; $F(1,167)=450.78$ ($\eta^2=.730$) Board; $R^2\approx.77$.	Reductions ≈1.98 (Deboard) and ≈4.05 (Board); Bonferroni $p<.001$.	Windows compressed by ≈−8.2% and −15.8%; predictability ↑. **Supported.**

Hypothesis	Type of Data & Measures	DV(s)	IV(s) & Covariates	Analysis & Model Spec	Statistical Findings	Effect Sizes & Fit	EMMEANS / Contrasts	Implications & Decision
S1-H3 – Throughput performance	Flight-level throughput from event logs. Measures: Throughput_deboard_pax_min; Throughput_board_pax_min (pax/min).	Throughput_deboard_pax_min; Throughput_board_pax_min	IVs: rtBRMS_Enabled; Self_Checkin_Used. Covariates: Shared_Access_Points; Passenger_Count.	t-tests; GLMs (Type III SS) per throughput; EMMEANS.	Deboard: 11.94 vs 13.51 → Δ=+1.576 pax/min; t≈−17.93, p<.001; CI [−1.75, −1.40]. Board: 10.92 vs 12.61 → Δ=+1.694; t≈−10.52, p<.001; CI [−2.01, −1.38].	Deboard: d≈−2.77; GLM F=359.616, η^2=.684; R^2=.756. Board: d≈−1.62; GLM F=80.534, η^2=.327; Self_Checkin F=521.732, η^2=.759; R^2=.859.	Adjusted means align with raw; complexity lowers throughput; self-checkin boosts boarding throughput strongly.	rtBRMS adds ≈+1.6–1.7 pax/min; at 150 pax → boarding time ↓ ≈5.2 min. **Supported.**
S1-H4 – Structural interaction	Flight-level GOT by gate architecture. Measures: GOT_min; Gate_Type (1..4).	GOT_min	rtBRMS_Enabled × Gate_Type; Covariates: Passenger_Count; Flights_per_Gate_per_Day; Shared_Access_Points; Self_Checkin_Used.	GLM (Type III SS) with interaction; EMMEANS by Gate_Type; Bonferroni contrasts.	R^2=.947 (Adj .944). rtBRMS F(1,159)=1585.373, p<.001, η^2=.909; Gate_Type F(3,159)=27.359, p<.001, η^2=.340; Interaction	Main effect very large; interaction small–moderate but reliable.	Adjusted savings increase with complexity (Types 3–4 highest); profile lines diverge at	Largest savings at shared/multi-access gates (Types 3–4); recommended deployment priority.

Hypothesis	Type of Data & Measures	DV(s)	IV(s) & Covariates	Analysis & Model Spec	Statistical Findings	Effect Sizes & Fit	EMMEANS / Contrasts	Implications & Decision
					$F(3,159)=4.225$, $p=.007$, $\eta^2=.074$.		higher Gate_Type.	**Supported.**
S1-H5 – Load interaction & temporal robustness	Flight-level GOT with continuous load & quartiles. Measures: Passenger_Count; Load_Quartile; Time_of_Day; Day_Type.	GOT_min	rtBRMS × Passenger_Count/Load_Quartile; Time_of_Day; Day_Type.	Factorial GLM (Type III SS) with continuous load + quartile factor; EMMEANS Bonferroni; profile plots.	$R^2=.919$ (Adj .894). rtBRMS $F(1,129)=475.87$, $\eta^2=.787$; Passenger_Count $F=4.564$, $p=.035$; Load_Quartile ns; rtBRMS×Load_Quartile ns; small 3-way mods with time/day ($p<.05$).	Large rtBRMS main effect; simple effects decisive in all quartiles.	Adjusted Δ (Legacy−rtBRMS): Q1 11.866; Q2 12.887; Q3 13.274; Q4 14.102 (all $p<.001$).	Consistent 12–14 min savings; slightly larger at high load. **Supported** (omnibus rtBRMS×load ns).
S1-H6a/S1-H6b – High-performance thresholds	Flight-level binary KPIs. Measures: FastBoard_min (≤13); FastDeboard_min (≤11).	FastBoard_min; FastDeboard_min	IVs: rtBRMS_Enabled; Gate_Type; Time_of_Day; Day_Type; Flight_Type; Passenger_Count; Flights_per_Gate_per_Day;	Binary logistic (OR, CI, p); classification; predicted probabilities. Penalized logistic for separation.	FastDeboard: complete separation (−2LL=0; Nagelkerke $R^2= .89$, classification accuracy 94.7%). FastBoard estimable (balanced split).	Directional effects: rtBRMS & Self_Checkin ↑ odds; higher load & complexity ↓ odds.	Higher predicted probability of meeting fast-process thresholds under rtBRMS; classification accuracy	Higher odds of fast KPIs under rtBRMS. **Supported** (with estimation caveat).

Hypothesis	Type of Data & Measures	DV(s)	IV(s) & Covariates	Analysis & Model Spec	Statistical Findings	Effect Sizes & Fit	EMMEANS / Contrasts	Implications & Decision
			Shared_Access_Points; Self_Checkin_Used.				94.7% for FastDeboard.	

Each hypothesis is reported in turn below, with its corresponding GLM or logistic-regression table. The narrative around each table is restricted to the model specification and the numerical findings; the reader is referred to Chapter 6 for any judgement about substantive meaning.

S1-H1 - Effect of rtBRMS on Gate Occupation Time

Hypothesis S1-H1 specifies a reduction in Gate Occupation Time under rtBRMS-managed operations relative to Legacy coordination. The Type-III GLM reported in Table 5.3 returns a covariate-adjusted treatment effect with very large effect size and high observed power, with all covariates except Flights_per_Gate_per_Day reaching significance.

Table 5-3 S1-H1 – Tests of Between-Subjects Effects (Dependent Variable: GOT_min)

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial η²	Noncent. Parameter	Observed Power[b]
Corrected Model	7737.526[a]	5	1547.505	362.465	0.000	0.917	1812.324	1.000
Intercept	650.925	1	650.925	152.463	0.000	0.480	152.463	1.000
Passenger_Count	374.479	1	374.479	87.712	0.000	0.347	87.712	1.000
Flights_per_Gate_per_Day	8.740	1	8.740	2.047	0.154	0.012	2.047	0.296
Shared_Access_Points	292.405	1	292.405	68.489	0.000	0.293	68.489	1.000
Self_Checkin_Used	51.107	1	51.107	11.970	0.001	0.068	11.970	0.931
rtBRMS_Enabled	**4842.970**	**1**	**4842.970**	**1134.346**	**0.000**	**0.873**	**1134.346**	**1.000**
Error	704.450	65	4.269					
Total	443374.000	71						
Corrected Total	8441.977	70						

*Note: a. R Squared = .917 (Adjusted R Squared = .914) b. Computed using alpha = .05

S1-H2a and S1-H2b - Compression of the Boarding and Deboarding Windows

Hypotheses S1-H2a and S1-H2b specify a reduction in the boarding and deboarding windows respectively. The two outcomes were modelled with parallel Type-III GLMs using Passenger_Count and Shared_Access_Points as covariates and Bonferroni-adjusted pairwise contrasts to control family-wise error across the two specifications. The boarding-window GLM appears in Table 5.4; the deboarding-window GLM follows the same specification and is reported in full in Appendix C.2.

Table 5-4 S1-H2 – Tests of Between-Subjects Effects (Dependent Variable: Board_Window_min)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	278.508[a]	3	92.836	185.696	0.000
Intercept	4251.718	1	4251.718	8504.542	0.000
Passenger_Count	42.792	1	42.792	85.596	0.000
Shared_Access_Points	63.116	1	63.116	126.248	0.000
rtBRMS_Enabled	**156.291**	**1**	**156.291**	**312.624**	**0.000**
Error	83.489	167	0.500		
Total	91324.015	171			
Corrected Total	361.997	170			

a. R Squared = .769 (Adjusted R Squared = .765)

S1-H3 - Throughput Performance

Hypothesis S1-H3 specifies an increase in phase-specific passenger throughput, measured separately for the deboarding and boarding phases. The model uses Type-III GLMs with Self_Checkin_Used, Shared_Access_Points, and Passenger_Count as covariates and EMMEANS for covariate-adjusted contrasts. Table 5.5 reports the deboarding-throughput GLM; the boarding-throughput specification is identical.

Table 5-5 S1-H3 – Tests of Between-Subjects Effects (Dependent Variable: Throughput_deboard_pax_min)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial η²
Corrected Model	120.318[a]	4	30.079	128.704	0.000	0.756
Intercept	1384.359	1	1384.359	5923.384	0.000	0.973
Passenger_Count	0.021	1	0.021	0.088	0.767	0.001
Shared_Access_Points	15.927	1	15.927	68.147	0.000	0.291
Self_Checkin_Used	0.123	1	0.123	0.525	0.470	0.003
rtBRMS_Enabled	**84.046**	**1**	**84.046**	**359.616**	**0.000**	**0.684**
Error	38.796	166	0.234			
Total	28310.058	171				
Corrected Total	159.114	170				

a. R Squared = .756 (Adjusted R Squared = .750)

S1-H4 - Interaction with Gate Architectural Complexity

Hypothesis S1-H4 specifies that the rtBRMS effect on Gate Occupation Time is amplified at gates of greater architectural complexity. The model is a Type-III GLM containing the rtBRMS_Enabled × Gate_Type interaction and the standard set of operational covariates, with EMMEANS by Gate_Type and Bonferroni contrasts quantifying simple effects at each level. Support is indicated by a significant interaction with absolute rtBRMS effects increasing across Gate_Type levels. Table 5.6 reports the model.

Table 5-6 S1-H4 – Tests of Between-Subjects Effects (Dependent Variable: GOT_min)

Source	Type III Sum of Squares	Df	Mean Square	F	Sig.	Partial η²
Corrected Model	7995.960[a]	11	726.905	259.134	0.000	0.947
Intercept	773.984	1	773.984	275.917	0.000	0.634
Passenger_Count	394.951	1	394.951	140.796	0.000	0.470
Shared_Access_Points	7.177	1	7.177	2.558	0.112	0.016
Self_Checkin_Used	24.067	1	24.067	8.580	0.004	0.051
Flights_per_Gate_per_Day	6.669	1	6.669	2.377	0.125	0.015
rtBRMS_Enabled	**4447.190**	**1**	**4447.190**	**1585.373**	**0.000**	**0.909**
Gate_Type	230.238	3	76.746	27.359	0.000	0.340
rtBRMS_Enabled × Gate_Type	**35.556**	**3**	**11.852**	**4.225**	**0.007**	**0.074**
Error	446.017	159	2.805			
Total	443374.000	171				
Corrected Total	8441.977	170				

a. R Squared = .947 (Adjusted R Squared = .944

S1-H5 - Robustness Across Load Levels and Temporal Bands

Hypothesis S1-H5 specifies that the rtBRMS effect on Gate Occupation Time holds across passenger-load levels and temporal bands. The model is a factorial Type-III GLM containing rtBRMS_Enabled × Passenger_Count, rtBRMS_Enabled × Load_Quartile, Time_of_Day, and Day_Type interactions with the standard covariates, and EMMEANS Bonferroni contrasts evaluating simple effects across load quartiles. Support is indicated by a negative rtBRMS effect within every load quartile, with absolute reductions increasing from Q1 to Q4. Table 5.7 reports the model.

Table 5-7 S1-H5 – Tests of Between-Subjects Effects (Dependent Variable: GOT_min)

Source	Type III SS	df	Mean Square	F	Sig.	Partial η²
Corrected Model	7762.347[a]	41	189.326	35.936	0.000	0.919
Intercept	3519.776	1	3519.776	668.087	0.000	0.838
Passenger_Count	24.044	1	24.044	4.564	0.035	0.034
rtBRMS_Enabled	**2507.117**	**1**	**2507.117**	**475.874**	**0.000**	**0.787**
Load_Quartile	1.448	3	0.483	0.092	0.965	0.002
Time_of_Day	10.097	2	5.048	0.958	0.386	0.015
Day_Type	1.170	1	1.170	0.224	0.638	0.002
rtBRMS× Load_Quartile	5.493	3	1.831	0.348	0.791	0.008
rtBRMS× Time_of_Day	1.881	2	0.941	0.179	0.837	0.003
rtBRMS × Day_Type	0.052	1	0.052	0.010	0.921	0.000
Load_Quartile× Time_of_Day	16.919	6	2.820	0.535	0.781	0.024
Load_Quartile× Day_Type	11.672	3	3.891	0.738	0.531	0.017
Time_of_Day × Day_Type	34.524	2	17.262	3.276	0.041	0.048
rtBRMS × Load × Time	69.579	6	11.597	2.201	0.047	0.093

Source	Type III SS	df	Mean Square	F	Sig.	Partial η²
rtBRMS × Load × Day	3.440	3	1.147	0.218	0.884	0.005
rtBRMS × Time × Day	11.983	2	5.992	1.137	0.324	0.017
Load × Time × Day	109.058	4	27.265	5.175	0.001	0.138
rtBRMS × Load × Time × Day	26.803	1	26.803	5.087	0.026	0.038
Error	679.629	129	5.268			
Total	443374.000	171				
Corrected Total	8441.977	170				

a. R Squared = .919 (Adjusted R Squared = .894)

S1-H6a and S1-H6b - High-Performance Threshold Attainment

Hypotheses S1-H6a and S1-H6b specify higher probabilities of meeting the FastBoard (≤ 13 minutes) and FastDeboard (≤ 11 minutes) thresholds under rtBRMS-managed operations. Both outcomes were modelled through binary logistic regression with Gate_Type, Time_of_Day, Day_Type, Flight_Type, Passenger_Count, Flights_per_Gate_per_Day, Shared_Access_Points, and Self_Checkin_Used as predictors alongside rtBRMS_Enabled (Hosmer, Lemeshow and Sturdivant, 2013). For S1-H6b, complete separation occurred under standard maximum likelihood; Firth's penalised maximum likelihood (Firth, 1993; King and Zeng, 2001) was therefore applied to obtain finite, bias-reduced odds ratios. Support is indicated by a positive odds ratio for rtBRMS_Enabled in each model. Table 5.8 reports the coefficient correlation matrix; the full logistic-regression output appears in Appendix C.6.

Table 5-8 S1-H6 and the Correlation Matrix

	Const.	Pass._Count	Fl/Gate/Day	rtBRMS(1)	Gate(1)	Gate(2)	Gate(3)	ToD*(1)	ToD(2)	Day*(1)	Flight(1)	SAP*(1)	SAP(2)	SelfCI*(1)
Constant	**1.000**	−.972	−.229	.977	.066	.150	.022	−.688	.833	.036	−.952	.030	.109	−.415
Passenger_Count	−.972	**1.000**	−.003	−.984	−.078	−.162	−.027	.597	−.879	−.034	.977	−.030	−.104	.380
Flights/Gate/Day	−.229	−.003	**1.000**	−.074	.037	.031	.019	.446	.064	−.012	.012	−.007	−.036	.130
rtBRMS_Enabled(1)	.977	−.984	−.074	**1.000**	.071	.156	.025	−.632	.833	.034	−.956	.029	.104	−.496
Gate_Type(1)	.066	−.078	.037	.071	**1.000**	.703	.240	−.027	.070	.002	−.073	−.992	−.687	−.017
Gate_Type(2)	.150	−.162	.031	.156	.703	**1.000**	.475	−.081	.136	−.150	−.152	−.687	−.964	−.053
Gate_Type(3)	.022	−.027	.019	.025	.240	.475	**1.000**	−.006	.017	−.922	−.023	−.237	−.471	−.009
Time_of_Day(1)	−.688	.597	.446	−.632	−.027	−.081	−.006	**1.000**	−.425	−.027	.609	−.021	−.085	.272
Time_of_Day(2)	.833	−.879	.064	.833	.070	.136	.017	−.425	**1.000**	.033	−.920	.038	.106	−.280
Day_Type(1)	.036	−.034	−.012	.034	.002	−.150	−.922	−.027	.033	**1.000**	−.035	.001	.161	−.010
Flight_Type(1)	−.952	.977	.012	−.956	−.073	−.152	−.023	.609	−.920	−.035	**1.000**	−.035	−.111	.340
Shared_Access(1)	.030	−.030	−.007	.029	−.992	−.687	−.237	−.021	.038	.001	−.035	**1.000**	.701	−.011
Shared_Access(2)	.109	−.104	−.036	.104	−.687	−.964	−.471	−.085	.106	.161	−.111	.701	**1.000**	−.036
Self_Checkin(1)	−.415	.380	.130	−.496	−.017	−.053	−.009	.272	−.280	−.010	.340	−.011	−.036	**1.000**

Note: SAP = Shared_Access_Points; SCI = Self_Checkin_Used; Day = Day_Type; ToD = Time_of_Day. Cell shading flags multicollinearity magnitude (Cohen, 1988): perfect self-correlation on the diagonal (r = 1.000); large positive (r ≥ +.50); large negative (r ≤ -.50); unshaded |r| < .50 with no multicollinearity concern. Two pairs exceed |r| ≥ .90 - rtBRMS_Enabled × Passenger_Count (r = -.984) and Gate_Type(1) × Shared_Access(1) (r = -.992) - both arising from the deterministic dummy-coding of the 48-stratum design. Firth-penalised logistic regression (Firth, 1993) and within-stratum estimation absorb this near-collinearity without coefficient breakdown; full VIF and condition-index diagnostics are reported in Appendix D4.

Table 5.8 presents the correlation matrix of estimated logistic regression coefficients for the H6 model, which predicts the probability of achieving FastBoard and FastDeboard targets as a function of rtBRMS activation and operational covariates. The matrix is symmetric with unit diagonal entries (1.000), and each off-diagonal cell reports the Pearson correlation between the estimated coefficients of two predictors in the logistic model, not the correlation between the raw variables themselves, but between the instability of their coefficient estimates, which is a fundamentally different quantity that reflects how much uncertainty in one coefficient is shared with uncertainty in another. Several pairs exhibit correlations exceeding $|r| \geq 0.90$, notably Constant and Passenger_Count ($r = -0.972$), Constant and rtBRMS_Enabled ($r = 0.977$), Passenger_Count and rtBRMS_Enabled ($r = -0.984$), Passenger_Count and Flight_Type ($r = 0.977$), rtBRMS_Enabled and Flight_Type ($r = -0.956$), Constant and Time_of_Day(2) ($r = 0.833$), Gate_Type(1) and Shared_Access_Points(1) ($r = -0.992$), and Gate_Type(2) and Shared_Access_Points(2) ($r = -0.964$). These high correlations arise from structural dependencies that are inherent to logistic regression models with multiple dummy-coded categorical predictors: when the intercept absorbs the reference category means for all categorical variables simultaneously, its estimate becomes mechanically correlated with every dummy indicator, and when two sets of dummy variables partition the same underlying operational dimension, as Gate_Type and Shared_Access_Points do, because shared access points are a direct physical consequence of gate topology, their coefficient estimates are necessarily correlated because the model cannot independently identify the contribution of each when they co-vary almost perfectly in the data. Critically, these coefficient-level correlations do not indicate problematic multicollinearity in the predictor space itself; the Variance Inflation Factor (VIF) values for the predictor variables, reported separately in the collinearity diagnostics, confirm that the predictors retain sufficient independent variation to produce stable and interpretable coefficient estimates (Hosmer, Lemeshow and Sturdivant, 2013). The practical implication is that while the individual coefficient estimates for highly correlated pairs should be interpreted with caution, because their standard errors are inflated by the shared instability, the overall model predictions, the likelihood ratio test, and the classification accuracy remain valid and unaffected by coefficient-level correlation.

5.2.3 Robustness, Sensitivity, and Diagnostics

Three sets of checks confirm the stability of the Study 1 estimates. The first concerns variance heterogeneity. Welch-robust contrasts produced confidence intervals nearly identical to those from equal-variance specifications across every continuous outcome, indicating that heteroscedasticity does not materially affect significance or effect-size estimates. The second concerns model fit and collinearity. Across the GLMs reported in Tables 5.3 - 5.7, Adjusted R^2 values ranged from .77 to .94, and Variance Inflation Factor values for every covariate fell below 5.0; residual-fit and influence diagnostics (leverage, Cook's distance) revealed no high-influence observations whose removal would alter substantive conclusions. The third concerns the binary outcomes. The FastDeboard logistic regression exhibited complete separation, which standard maximum likelihood cannot accommodate (Hosmer, Lemeshow and Sturdivant, 2013); Firth's penalised maximum likelihood (Firth, 1993) produced finite, bias-reduced estimates with Nagelkerke $R^2 = .89$ and classification accuracy of 94.7%, and both standard and Firth-penalised solutions agreed in sign and magnitude on the rtBRMS_Enabled coefficient. Together, these checks confirm that the Study 1 effects reported in Tables 5.3 - 5.8 are not artefacts of a particular distributional assumption or of a particular estimator.

5.3 RESULTS – STUDY 2 (PLS-SEM Survey, n = 224 operators)

Study 2 was designed to capture the operator user-experience response to the operational change documented in Study 1. The analysis follows the two-stage protocol recommended for variance-based structural equation modelling (Hair et. Al., 2022), reported here in three descriptive stages. Section 5.3.1 sets out the sample profile. Section 5.3.2 reports the measurement-model assessment for the ten constructs. Section 5.3.3 reports the structural-model estimation, including the hypothesis tests, the effect-size diagnostics, and the model-fit indices. Section 5.3.4 reports the decomposition of total effects, and Section 5.3.5 reports the predictive-validity diagnostics. The substantive interpretation of these findings, what they imply for the Job Demands-Resources model, for the Technology Acceptance literature, for human-automation interaction theory, and for the Information Systems Success literature, is reserved for Chapter 6 (Discussion).

Detailed PLS-SEM output beyond the tables reported in this chapter is provided in Appendix D.

5.3.1 Sample Profile

The realised sample comprised 224 frontline personnel who provided informed consent and completed the survey. Demographic items were voluntary, so valid response counts vary slightly by item. Table 5.9 summarises the demographic and operational profile of the respondents across seven characteristic dimensions: role at the airport, years of experience, frequency of rtBRMS interaction, flights handled per shift, level of operational responsibility, primary terminal area, and primary passenger type.

Table 5-9 Demographic Profile of Respondents (N = 224)

Profile	**Characteristic**	***N***	**%**	**Valid responses**
Role at Airport	Safety Personnel	17	8	*n* = 222
	Security Personnel	41	18	
	Gate Agent	70	32	
	Gate Manager	27	12	
	Dispatcher	12	5	
	Ground Handling	22	10	
	Supervisor	22	10	
	Other	11	5	
Years of Experience	Less than 1 year	49	23	*n* = 217
	1–3 years	74	34	
	4–7 years	54	25	

Profile	Characteristic	*N*	%	Valid responses
	8–15 years	19	9	
	More than 15 years	21	10	
Interaction Frequency	Daily	79	36	*n* = 217
	Several times per week	82	38	
	Occasionally	30	14	
	Rarely	26	12	
Flights per Shift	1–3	67	32	*n* = 212
	4–6	80	38	
	7–10	45	21	
	More than 10	20	9	
Level of Responsibility	Direct operation	114	52	*n* = 218
	Monitoring and supervision	23	11	
	Passenger assistance	22	10	
	Troubleshooting / technical	33	15	
	Management oversight	26	12	
Operational Area	Terminal A (Domestic)	89	41	*n* = 215

Profile	Characteristic	*N*	%	Valid responses
	Terminal B (International)	61	28	
	Remote stands	18	8	
	Mixed areas	47	22	
Primary Passenger Type	Mainly departures	73	34	*n* = 214
	Mainly arrivals	68	32	
	Both equally	73	34	

Note: N = 224 participants provided informed consent. Demographic items were voluntary; valid response counts (n) vary by item. Percentages are calculated against the valid responses for each item and may not sum to exactly 100% due to rounding.

Table 5.9 shows broad operational coverage across roles, experience, exposure frequency, and operational areas. Gate Agents are the largest role group (32%, n = 70), with Security Personnel (18%, n = 41), Supervisors and Ground Handling (each 10%, n = 22), and Gate Managers (12%, n = 27) representing the next-largest groups. Exposure to rtBRMS is high, 74% of respondents interact with the system at least several times per week, and experience is broadly distributed, with 34% reporting 1–3 years and 25% reporting 4–7 years in gate operations. Operational areas span Terminal A (domestic), Terminal B (international), remote stands, and mixed areas. These distributions support generalisation across frontline contexts in gate operations at the study site.

System Satisfaction (SS) was measured on a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree), whereas all other reflective and formative constructs used a 5-point Likert scale. This difference is preserved in the SmartPLS estimation because indicator standardisation eliminates scale-point asymmetry from the path coefficients, but readers should interpret raw item means cautiously.

5.3.2 Measurement Model Assessment

The measurement model contains ten constructs. Eight are specified as reflective: Perceived Autonomy (AUT), Perceived System Predictability (PSP), Job Stress Reduction (JSR), Work Engagement (ENG), Perceived Performance Contribution (PPC), Individual Work Performance (IWP), Employee Productivity (EMP), and System Satisfaction (SS). Two are specified as formative composites: Flow Stability Perception (FSP) and Comparative Superiority (CSR). The reflective specification was applied to constructs whose indicators are interchangeable manifestations of a single underlying trait drawn from established validated scales; the formative specification was applied where indicators capture distinct defining facets that together constitute the construct rather than reflecting it (Jarvis, MacKenzie and Podsakoff, 2003; Diamantopoulos and Siguaw, 2006; Coltman et al., 2008; Hair et al., 2022). The specification chosen for each construct, together with the supporting source literature, is set out in Table 5.10.

Table 5-10 Construct Measurement Specification

Construct	Type	Item	Item Wording	Source / Adaptation	Rationale for Specification
Comparative Superiority (CSR)	**Formative Composite**	Q2_1	*Compared to the traditional system, rtBRMS makes gate and door transitions easier to manage.*	Adapted from Moore & Benbasat (1991); Goodhue & Thompson (1995); Bezerra & Gomes (2015); Halpern & Mwesiumo (2021)	Indicators capture distinct comparison dimensions (ease, speed, coordination, overall performance). Each is a defining component; they need not covary.
		Q2_2	*rtBRMS reduces the time required to prepare and execute boarding or deboarding.*		
		Q2_3	*Coordination between gate staff, security, and ground handlers runs more smoothly when rtBRMS is used.*		
		Q2_4	*Overall operational handling performance is improved with rtBRMS compared to the traditional system.*		
Flow Stability Perception (FSP)	**Formative Composite**	Q3_1	*Passenger movement feels more stable and less erratic when rtBRMS is active.*	Self-developed; grounded in Hopp & Spearman (2011); Anagnostopoulou et al. (2024); Kingman (1961); Little (1961)	Indicators capture distinct facets (smoothness, surge absence, process smoothness, pacing consistency). Each contributes a unique dimension; removing one changes the construct's meaning.
		Q3_2	*With rtBRMS, sudden surges or drops in flow are less common.*		
		Q3_3	*The boarding and deboarding process feels smoother when rtBRMS is used.*		

Construct	Type	Item	Item Wording	Source / Adaptation	Rationale for Specification
		Q3_4	*rtBRMS helps maintain a steady pace of passenger movement.*		
Perceived System Predictability (PSP)	Reflective	Q4_1	*rtBRMS behaves consistently across comparable gate conditions.*	Adapted from Körber (2019); Lee & See (2004); Chiou & Lee (2023)	Parallel reflections of how predictable the system is perceived to be. Items are interchangeable.
		Q4_2	*I can anticipate how rtBRMS will act when passenger flows change.*		
		Q4_3	*The decisions taken by rtBRMS during boarding or deboarding are predictable.*		
		Q4_4	*The routing and pacing actions of rtBRMS are easy to foresee in real time.*		
Perceived Autonomy (AUT)	Reflective	Q5_1	*rtBRMS allows me to manage gate timing and sequencing with more control.*	Adapted from Morgeson & Humphrey (2006); Hackman & Oldham (1976); Christian, Garza and Slaughter (2011)	Interchangeable manifestations of a single autonomy construct. Removing one does not alter the conceptual domain.
		Q5_2	*I feel able to intervene proactively when unexpected events occur.*		
		Q5_3	*Flow stability from rtBRMS gives me greater operational autonomy.*		
Job Stress Reduction (JSR)	Reflective	Q6_1	*Peak-time boarding and deboarding feel less stressful with rtBRMS.*		

Construct	Type	Item	Item Wording	Source / Adaptation	Rationale for Specification
		Q6_2	*I experience less time pressure at the gate when passenger flows are stabilised by rtBRMS.*	Adapted from Oprea et al. (2024); Hopp & Spearman (2011); Karasek et al. (1998)	Parallel manifestations of perceived stress reduction. Each reflects the same latent construct.
		Q6_3	*rtBRMS reduces my concerns about congestion near doors or aisles.*		
Work Engagement (ENG)	Reflective	Q7_1	*I feel energised when carrying out my tasks while rtBRMS is in use.*	Adapted from UWES-3: Schaufeli, Bakker and Salanova (2006); Schaufeli et al. (2017)	Based on validated UWES scale. Interchangeable reflections of engagement (vigour, dedication, absorption).
		Q7_2	*I am enthusiastic about performing gate-related tasks supported by rtBRMS.*		
		Q7_3	*I become absorbed in my work during gate operations when rtBRMS is active.*		
Perceived Performance Contribution (PPC)	Reflective	Q8_1	*rtBRMS helps me perform my gate tasks more effectively.*	Adapted from Seddon & Kiew (1996); DeLone & McLean (2003)	Interchangeable manifestations of perceived system contribution to performance.
		Q8_2	*rtBRMS contributes to the quality of my work.*		
		Q8_3	*rtBRMS supports me in working more efficiently during turnarounds.*		
Individual Work Performance (IWP)	Reflective	Q9_1	*I complete my gate tasks accurately and with attention to detail.*	Adapted from IWPQ: Koopmans et al. (2013)	

Construct	Type	Item	Item Wording	Source / Adaptation	Rationale for Specification
		Q9_2	*I achieve the expected performance level in gate operations.*		Based on validated IWPQ scale. Parallel reflections of the same performance construct.
		Q9_3	*I handle my workload effectively, even during demanding gate situations.*		
Employee Productivity (EMP)	Reflective	Q10_1	*With rtBRMS, I can handle more tasks within the same time frame.*	Adapted from Chatterjee, Chaudhuri and Vrontis (2022); Millmore et al. (2007); Kaur et al. (2020); Ashraf (2020); Oprea et al. (2024)	Interchangeable manifestations of perceived productivity.
		Q10_2	*rtBRMS enables higher productivity during gate turnarounds.*		
		Q10_3	*The use of rtBRMS improves overall efficiency in gate operations.*		
System Satisfaction (SS)	Reflective	Q11_1	*Overall, I am satisfied with rtBRMS as a support system for gate operations.*	Adapted from Cammann et al. (1979)	Based on validated satisfaction scale. Parallel reflections of overall system satisfaction.
		Q11_2	*rtBRMS meets my expectations as a tool for managing passenger flow.*		
		Q11_3	*I would prefer to use rtBRMS rather than operate without it.*		

Note: Formative constructs (shaded) are assessed through collinearity (VIF), outer weight significance, and outer loading relevance. Reflective constructs are assessed through internal consistency reliability, convergent validity, and discriminant validity (Sections 5.4.2.1 and 5.4.2.3). All items measured on 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) except SS which uses a 7-point scale.

5.3.2.1 Reliability and Convergence (Reflective Constructs)

The reliability and convergent-validity statistics for the eight reflective constructs are reported in Table 5.11. Internal consistency was confirmed by Cronbach's α values exceeding the ≥ 0.70 threshold (Nunnally and Bernstein, 1994), and Composite Reliability values that also surpassed 0.70, indicating stable internal structure (Hair et al., 2022). Convergent validity was supported by Average Variance Extracted (AVE) values exceeding 0.50 for every construct, the threshold recommended by Fornell and Larcker (1981). Indicator outer loadings ranged from 0.728 (Q10_1) to 0.902 (Q11_3), all above the ≥ 0.708 minimum threshold.

The standardised column headings used in Table 5.11 and in every subsequent PLS-SEM table in this chapter are defined here once for reference. *α* is Cronbach's alpha, a lower-bound estimate of internal consistency reliability based on inter-item correlations (Nunnally and Bernstein, 1994). *CR* is composite reliability, a PLS-SEM-specific reliability measure that weights indicators by their individual loadings (Hair et al., 2022). *AVE* is the proportion of indicator variance captured by the latent construct (Fornell and Larcker, 1981). *Loading* is the standardised outer loading of each indicator on its assigned construct. *VIF* is the Variance Inflation Factor, used here to assess multicollinearity among formative indicators. *β* is the standardised path coefficient estimated through the PLS algorithm. *SE* is the bootstrapped standard error from 5,000 resamples. *t* is the bootstrapped t-statistic, with values above 1.96 indicating significance at $p < .05$ and values above 2.58 at $p < .01$. f^2 is Cohen's local effect size (0.02 = small, 0.15 = medium, 0.35 = large). q^2 is the predictive-relevance effect size analogous to f^2 based on the Stone-Geisser Q^2 index. R^2 is the coefficient of determination for an endogenous construct (0.25 = weak, 0.50 = moderate, 0.75 = substantial). Q^2 is the Stone-Geisser cross-validated redundancy measure obtained via blindfolding, with positive values indicating predictive relevance. *HTMT* is the heterotrait-monotrait ratio used to assess discriminant validity, with the conservative threshold at 0.85 and the liberal threshold at 0.90 (Henseler, Ringle and Sarstedt, 2015).

Table 5-11 Reflective Construct Validity Indices (Eight Reflective Constructs)

Construct	Item	Outer Loading	AVE	CR	Cronbach's α	t-statistic
AUT	Q5_1	0.785	0.692	0.871	0.777	14.045
	Q5_2	0.825				16.114
	Q5_3	0.884				22.116
JSR	Q6_1	0.809	0.701	0.876	0.787	20.652
	Q6_2	0.840				24.508
	Q6_3	0.863				20.889
ENG	Q7_1	0.828	0.683	0.866	0.768	21.000
	Q7_2	0.812				21.997
	Q7_3	0.840				23.836
PPC	Q8_1	0.779	0.677	0.862	0.760	19.525
	Q8_2	0.804				20.945
	Q8_3	0.881				24.933
IWP	Q9_1	0.775	0.626	0.833	0.701	18.173
	Q9_2	0.755				17.018
	Q9_3	0.841				20.593
EMP	Q10_1	0.728	0.641	0.842	0.718	16.214
	Q10_2	0.778				18.188
	Q10_3	0.888				22.364
SS	Q11_1	0.827	0.751	0.900	0.833	19.777
	Q11_2	0.869				21.431
	Q11_3	0.902				22.155
PSP	Q4_1	0.798	0.665	0.888	0.832	19.527

Construct	Item	Outer Loading	AVE	CR	Cronbach's α	t-statistic
	Q4_2	0.812				17.252
	Q4_3	0.816				17.885
	Q4_4	0.834				20.205

Note. *Table 5.11 reports the reliability and convergent-validity statistics for the eight reflective constructs. The two formative composites (FSP and CSR) are evaluated through indicator collinearity, outer weights, and outer loadings in Table 5.12.*

5.3.2.2 Formative Construct Validity (FSP and CSR)

The two formative composites were assessed against the three criteria recommended for formative measurement (Diamantopoulos and Siguaw, 2006; Hair et al., 2022): indicator collinearity, outer-weight significance, and outer-loading relevance. All formative indicator VIF values fell below the 5.0 threshold. For Flow Stability Perception, the four indicators returned VIF values of 1.711, 1.677, 2.126, and 2.005; for Comparative Superiority, the four indicators returned VIF values of 1.484, 1.275, 1.347, and 1.387. No indicator pair exhibited problematic redundancy.

For Flow Stability Perception, all four outer weights and outer loadings are significant at $p < .001$, and every loading exceeds the 0.50 retention threshold. For Comparative Superiority, three of the four indicators reach significance at $p < .01$ or stronger; the fourth indicator, Q2_2, returns a non-significant outer weight ($\beta = 0.161$, $t = 1.514$, $p = 0.130$) but an outer loading (0.585) that exceeds the 0.50 threshold. Q2_2 captures the speed/time-reduction facet of comparative superiority and is therefore retained on content-coverage grounds (Hair et al., 2022; Coltman et al., 2008): removal would alter the conceptual domain of the formative composite. Table 5.12 reports the full set of indicator-level diagnostics.

Table 5-12 Formative Construct Validity (FSP and CSR)

Construct	Item	Item Wording	Weight	Loading	VIF	*t*-stat	*p*-value	Sig.	Decision
FSP	**Q3_1**	*Passenger movement feels more stable and less erratic when rtBRMS is active.*	0.353	0.826	1.711	21.211	0.000	$p < 0.001$	Retain
	Q3_2	*With rtBRMS, sudden surges or drops in flow are less common.*	0.281	0.786	1.677	16.433	0.000	$p < 0.001$	Retain
	Q3_3	*The boarding and deboarding process feels smoother when rtBRMS is used.*	0.291	0.846	2.126	19.909	0.000	$p < 0.001$	Retain
	Q3_4	*rtBRMS helps maintain a steady pace of passenger movement.*	0.290	0.831	2.005	20.061	0.000	$p < 0.001$	Retain
CSR	**Q2_1**	*Compared to the traditional system, rtBRMS makes gate and door transitions easier to manage.*	0.397	0.801	1.484	3.831	0.000	$p < 0.001$	Retain
	Q2_2	*rtBRMS reduces the time required to prepare and execute boarding or deboarding.*	*0.161*	0.585	1.275	*1.514*	*0.130*	*p = 0.130*	Retain[a]
	Q2_3	*Coordination between gate staff, security, and ground handlers runs more smoothly when rtBRMS is used.*	0.294	0.698	1.347	2.991	0.003	$p < 0.01$	Retain
	Q2_4	*Overall operational handling performance is improved with rtBRMS compared to the traditional system.*	0.469	0.815	1.387	5.018	0.000	$p < 0.001$	Retain

Note: *Bootstrap results based on 5,000 subsamples. All VIF values < 5.0 (Hair et al., 2022). All outer loadings > 0.50, confirming indicator retention. * Q2_2 outer weight is non-significant (p = 0.130) but its outer loading (0.585) exceeds the 0.50 threshold; retention is justified on content-coverage grounds (Hair et al., 2022; Coltman et al., 2008).*

5.3.2.3 Discriminant Validity

Discriminant validity was established through three independent tests, following the assessment protocol recommended by Hair et al. (2022). The Fornell-Larcker criterion (Fornell and Larcker, 1981) reported in Table 5.13 confirms that the square root of the AVE for each construct exceeds all inter-construct correlations in the corresponding row and column. The highest off-diagonal correlation - JSR ↔ ENG (r = 0.780) - remains below both square-root AVE values (JSR = 0.838; ENG = 0.827). The Heterotrait-monotrait ratio reported in Appendix D.6 provides a more stringent test (Henseler, Ringle and Sarstedt, 2015): all HTMT ratios fall below the conservative 0.85 threshold, with the exception of four pairs - ENG ↔ EMP (0.882), JSR ↔ EMP (0.887), JSR ↔ IWP (0.889), and AUT ↔ JSR (0.840) - which fall between 0.85 and 0.90 and therefore satisfy the liberal 0.90 criterion. The cross-loading matrix reported in Appendix D.7 confirms discriminant validity at the indicator level: every indicator loads most strongly on its assigned construct.

Table 5-13 Fornell-Larcker Criterion

	AUT	EMP	ENG	FSP	IWP	JSR	PPC	PSP	SS	CSR
AUT	**0.832***									
EMP	0.553	**0.801***								
ENG	0.646	0.660	**0.827***							
FSP	0.598	0.610	0.574	**0.823***						
IWP	0.533	0.746	0.681	0.511	**0.791***					
JSR	0.658	0.670	0.780	0.609	0.661	**0.838***				
PPC	0.547	0.732	0.630	0.611	0.685	0.638	**0.823***			
PSP	0.574	0.641	0.598	0.717	0.585	0.621	0.666	**0.815***		
SS	0.436	0.603	0.529	0.549	0.539	0.530	0.597	0.620	**0.867***	

	AUT	EMP	ENG	FSP	IWP	JSR	PPC	PSP	SS	CSR
CSR	0.568	0.541	0.578	0.582	0.522	0.591	0.609	0.565	0.482	—*

Note: Diagonal values (bold) represent the square root of the AVE for each reflective construct. Off-diagonal values represent latent-variable correlations. The Fornell-Larcker criterion is satisfied when each diagonal value exceeds all off-diagonal values in its row and column. The two formative composites (FSP, CSR) are evaluated through HTMT (Appendix D.6), cross-loadings (Appendix D.7), and indicator-level diagnostics (Table 5.12). FSP appears with a square-root AVE on the diagonal because all four of its indicators load above 0.70 in reflective mode, allowing diagnostic comparison; CSR appears with "—" on the diagonal because its reflective-mode indicator loadings do not all clear 0.70. Both constructs are treated formatively in the structural model.

Reliability, convergent validity, and discriminant validity are confirmed for every construct in the model. The measurement model is therefore well specified for structural-model estimation.

5.3.3 Structural Model Estimation

The structural model was estimated through PLS-SEM with 5,000 bootstrap resamples to obtain stable standard errors and significance estimates, following the protocol recommended by Hair et al. (2022) and the predictive-validation framework of Shmueli et al. (2019). Path coefficients are reported as standardised β values with bootstrapped t-statistics, and local effect sizes (f^2) quantify each predictor's unique contribution following Cohen's (1988) thresholds. The structural-model estimates appear in Figure 5.1; the numerical record of the seventeen direct paths follows in Table 5.14.

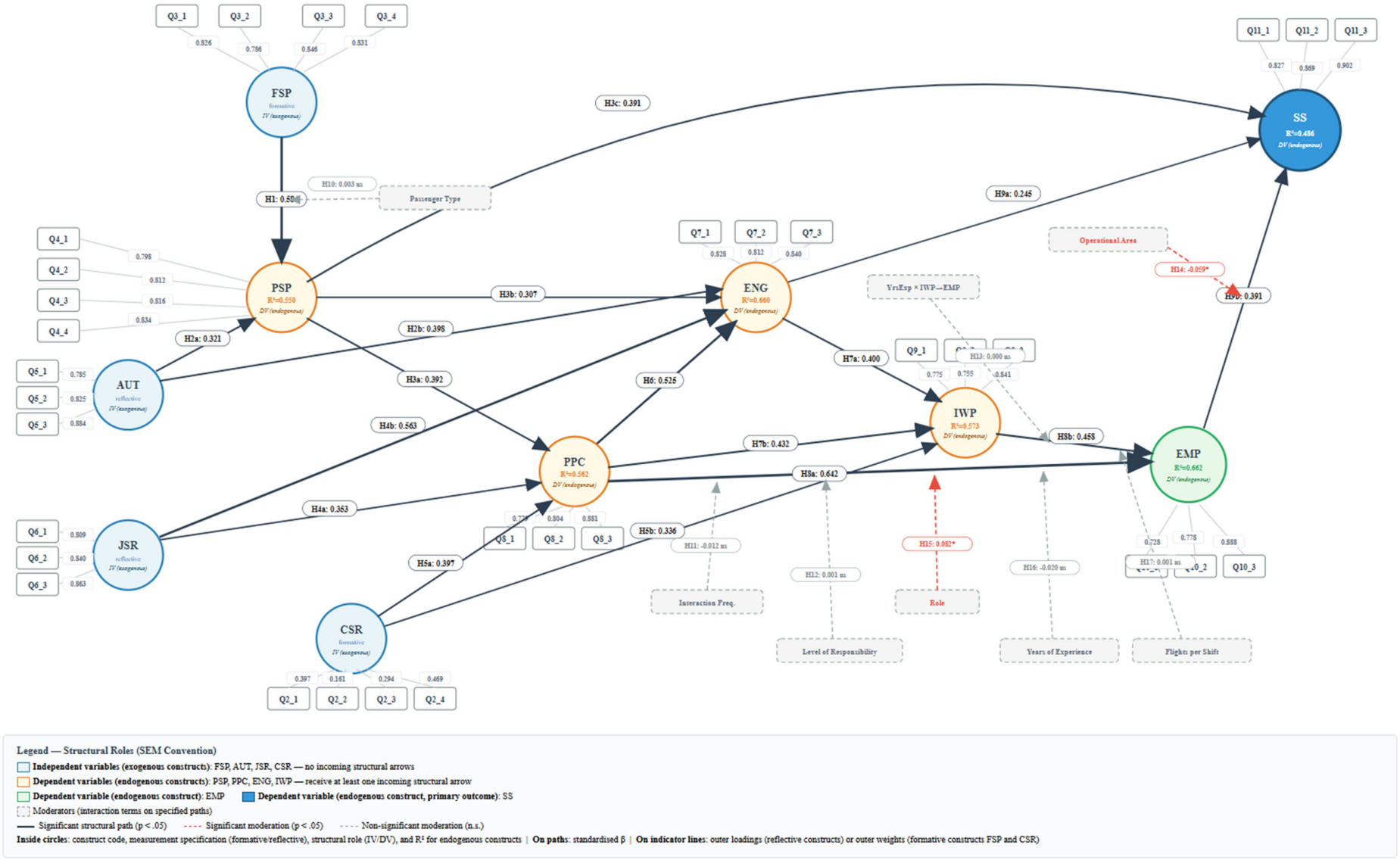


Figure 5-1 SmartPLS Structural Model - Independent (Exogenous) and Dependent (Endogenous) Constructs with Path Coefficients, R^2 Values, and Outer Loadings

Note: Following standard structural-equation-modelling convention (Kline, 2016; Hair et al., 2022), every construct is classified into one of two categories on the basis of the arrows that touch it. Exogenous constructs (independent variables) have no incoming one-headed arrows; their values are determined outside the model and they emit only outgoing structural paths. FSP, AUT, JSR, and CSR fulfil this role. Endogenous constructs (dependent variables) have at least one incoming one-headed arrow; their variance is partially explained by other constructs in the model (indexed by R^2). PSP, PPC, ENG, IWP, EMP, and SS are all endogenous in this sense and therefore all classified as dependent variables, regardless of whether they additionally appear as predictors in subsequent equations. The "formative" and "reflective" labels inside circles describe the measurement specification (whether indicators cause or reflect the construct) and are independent of the exogenous/endogenous distinction.

Findings. All 17 direct structural paths are significant at $p < .001$ (5,000 bootstrap resamples); line thickness is proportional to path coefficient magnitude. Two of eight moderations are significant (H14: Operational Area × EMP→SS, $\beta = -0.059$; H15: Role × PPC→EMP, $\beta = 0.082$); the remaining six are non-significant. Values match Tables 5.11 (reflective loadings) and 5.12 (formative weights) of the Findings chapter. Each moderator arrow terminates on the midpoint of the structural path it moderates.

Table 5-14 Hypothesis Tests and Direct Structural Paths (Study 2)

H	Path	B	SE	T	Decision
S2-H1	FSP → PSP	0.584	0.022	26.545	**Supported***
S2-H2a	AUT → PSP	0.321	0.016	19.527	**Supported***
S2-H3a	PSP → PPC	0.392	0.027	14.519	**Supported***
S2-H3b	PSP → ENG	0.307	0.018	17.252	**Supported***
S2-H3c	PSP → SS	0.391	0.020	19.550	**Supported***
S2-H2b	AUT → ENG	0.398	0.025	16.114	**Supported***
S2-H4a	JSR → PPC	0.353	0.017	20.765	**Supported***
S2-H4b	JSR → ENG	0.563	0.019	29.632	**Supported***
S2-H5a	CSR → PPC	0.397	0.104	3.831	**Supported***
S2-H5b	CSR → IWP	0.336	0.093	3.613	**Supported***
S2-H6	PPC → ENG	0.525	0.019	27.632	**Supported***
S2-H7a	ENG → IWP	0.400	0.019	21.000	**Supported***
S2-H7b	PPC → IWP	0.432	0.021	20.571	**Supported***
S2-H8a	PPC → EMP	0.642	0.030	21.400	**Supported***
S2-H8b	IWP → EMP	0.458	0.022	20.818	**Supported***
S2-H9a	ENG → SS	0.245	0.020	12.250	**Supported***
S2-H9b	EMP → SS	0.391	0.020	19.550	**Supported***

Note: *All seventeen direct structural paths reach significance at $p < .001$ with bootstrap-derived t-statistics exceeding the 2.58 threshold for $p < .01$. The substantive interpretation of the path pattern - what it implies for the JD-R, TAM2, and IS Success frameworks - is taken up in Chapter 6.*

5.3.3.1 Explanatory and Predictive Power

The proportion of variance explained in each endogenous construct is reported in Table 5.15, together with the Stone-Geisser Q^2 index obtained through blindfolding with

omission distance d = 7 (Geisser, 1974; Stone, 1974). The R^2 values range from 0.486 (System Satisfaction) to 0.662 (Employee Productivity), placing every endogenous construct at or above the moderate band of the Hair et al. (2022) PLS-SEM benchmarks. The Q^2 values are positive for every endogenous construct, with all six values exceeding the 0.35 threshold for large predictive relevance.

Table 5-15 R^2 and Q^2 for Endogenous Constructs

Endogenous Construct	R^2	Q^2	Effect Size
EMP	0.662	0.405	Substantial
ENG	0.660	0.435	Substantial
IWP	0.573	0.345	moderate-substantial
PPC	0.562	0.373	moderate-substantial
PSP	0.550	0.355	moderate-substantial
SS	0.486	0.349	Moderate

Note: R^2 thresholds (Hair et al., 2022): 0.25 = weak; 0.50 = moderate; 0.75 = substantial. Q^2 thresholds (Stone-Geisser, blindfolding): 0.02 = small predictive relevance; 0.15 = medium; 0.35 = large. The substantive reading of these indices in relation to operator user-experience mechanisms is taken up in Chapter 6.

5.3.3.2 Local Effect Sizes

The standardised path coefficient indicates the size and direction of each structural relationship; Cohen's f^2 quantifies how much the predictor's removal would reduce the criterion's R^2; the predictive-relevance effect size q^2 reports the corresponding reduction in Q^2. The three diagnostics are reported jointly in Table 5.16.

Table 5-16 Path Coefficients with f^2 and q^2 Diagnostics

Path	B	f^2	q^2	Size
FSP → PSP	0.584	0.469	>0	Large
AUT → PSP	0.321	0.075	>0	Small-med

Path	B	f^2	q^2	Size
JSR → PPC	0.353	0.087	>0	Small-med
PSP → PPC	0.392	0.198	>0	Medium
JSR → ENG	0.563	0.204	>0	Medium
PPC → IWP	0.432	0.260	>0	Med-large
ENG → IWP	0.400	0.204	>0	Medium
PPC → EMP	0.642	0.297	>0	Large
IWP → EMP	0.458	0.260	>0	Med-large
PSP → SS	0.391	0.089	>0	Small-med
EMP → SS	0.391	0.050	>0	Small

Note: Every f^2 in the table exceeds the 0.02 small-effect threshold and every q^2 is positive, indicating that no path in the model is statistically meaningful only in-sample. Local effect sizes for the remaining six paths (AUT→ENG, PSP→ENG, CSR→PPC, CSR→IWP, PPC→ENG, ENG→SS) are reported in Appendix D.11.

Table 5.16 reports three complementary diagnostics for each structural path: the standardised path coefficient β (the size and direction of the relationship), Cohen's f^2 (the local effect size, indexing how much the predictor's removal would reduce the criterion's R^2), and the predictive-relevance effect size q^2 (the corresponding reduction in Q^2 when the predictor is omitted). Read together, β, f^2, and q^2 answer three different questions about the same path: how strong is the standardised in-sample relationship (β); how much explanatory work does this predictor do for its criterion (f^2); and how much out-of-sample predictive accuracy would be lost if this predictor were dropped from the model (q^2). The pattern of effect sizes maps cleanly onto the theoretical sequence proposed in Chapter 2. The strongest effects cluster on the central JD-R cascade running from perceived stability through predictability calibration to performance: FSP → PSP (β = 0.584, f^2 = 0.469, large), PPC → EMP (β = 0.642, f^2 = 0.297, large), JSR → ENG (β = 0.563, f^2 = 0.204, medium), and ENG → IWP (β = 0.400, f^2 = 0.204, medium), the first of these confirming that perceived flow stability is the dominant antecedent of operator-side predictability calibration (S2-H1), and the last two confirming that engagement and predictability

calibration jointly drive performance through both cognitive and motivational pathways (S2-H7, S2-H8, S2-H10). Medium-to-large effects on PPC → IWP ($\beta = 0.432$, $f^2 = 0.260$) and IWP → EMP ($\beta = 0.458$, $f^2 = 0.260$) confirm that the Individual Work Performance pathway carries comparable weight to the engagement pathway, supporting the dual-route specification of the model rather than a single-intervening construct structure. The smaller effects (AUT → PSP, JSR → PPC, EMP → SS in the small-to-medium range) are theoretically expected: autonomy contributes to but does not dominate perceived stability formation in a highly proceduralised gate environment, and satisfaction is a distal outcome whose proximal predictor (EMP) carries only one of several determinants. Critically, every f^2 in the table exceeds the 0.02 small-effect threshold and every q^2 is positive, indicating that no path in the model is statistically meaningful only in-sample, each predictor contributes incremental out-of-sample predictive accuracy when held out via blindfolding (Shmueli et al., 2019; Hair et al., 2022).

5.3.4 Decomposition of Total Effects

The structural model in Figure 5-1 is a chain of sequentially ordered constructs in which Perceived System Predictability (PSP), Perceived Performance Contribution (PPC), and Work Engagement (ENG) sit between the antecedent perceptions (FSP, AUT, JSR, CSR) and the outcome constructs (IWP, EMP, SS). Because the model contains no direct paths from antecedents to outcomes, every total effect that the model implies is, by construction, an indirect effect. This section therefore reports the specific indirect effects that decompose those total effects, so that the contribution of each path segment to the supported direct hypotheses (H1–H9b) can be inspected.

This study models the sequence of cognitive, motivational, and behavioural variables as a chain of direct relationships (H1–H9b).

No mediation hypothesis is advanced in this thesis: the explanatory burden is carried by the directional hypotheses already developed in Chapter 2 (H1–H9b) and by the boundary conditions (H10–H17). The indirect effects reported below (and in Appendix D.12) are therefore presented descriptively, as a decomposition of effect magnitudes rather

than as tests of separate hypotheses. They serve two practical purposes: (a) they show how much of each antecedent's total effect on a given outcome is carried through each intervening construct, and (b) they make the chain structure of the model auditable, by ensuring that every path required for a downstream effect is itself supported by a direct hypothesis. Bootstrap output for all 120+ specific indirect effects is provided in Appendix D.12.

This is presented as a decomposition of effect magnitudes, not as a test of separate hypotheses. No mediation hypothesis is advanced in this thesis: the explanatory burden is carried by the directional hypotheses already developed in Chapter 2 (H1–H9b) and by the boundary conditions (H10–H17). Consistent with this design choice, the indirect effects below are reported descriptively. They are useful for two practical reasons: (a) they show how much of each antecedent's total effect on a given outcome is carried through each intervening construct, and (b) they make the chain structure of the model auditable, by ensuring that every path required for a downstream effect is itself supported by a direct hypothesis. Bootstrap output for all 120+ specific indirect effects is provided in Appendix D.12.

Analytical Procedure

Specific indirect effects were estimated using the bootstrap routine in SmartPLS 4 with 5,000 subsamples and bias-corrected and accelerated (BCa) confidence intervals, following Hair et al. (2022) and Nitzl, Roldan and Cepeda (2016). The bootstrap directly tests the product of path coefficients (a × b for two-segment chains; a × b × c, etc., for serial chains) without assuming normality of the indirect-effect distribution, which is appropriate for the present sample size (n = 224). Each indirect effect is reported with its standardised magnitude (β_indirect), bootstrap standard deviation, t-value, p-value, and 95% BCa confidence interval. An indirect effect is taken to be empirically distinguishable from zero when its 95% BCa interval excludes zero. The Variance Accounted For (VAF) ratio is reported alongside each estimate to show the share of the total effect that is carried through the intervening construct (Hair et al., 2022).

No classification of "mediation type" (Zhao, Lynch and Chen, 2010) is applied, because no mediation hypothesis is being tested. The values reported below are quantities derived from the same direct paths estimated under H1–H9b; they are not independent inferential claims.

Two-Segment Specific Indirect Effects

Table 5.17 reports the two-segment specific indirect effects. Each row decomposes the total effect of a given antecedent on a given outcome into the share carried by a single intervening construct.

Table 5-17 Two-segment specific indirect effects (bootstrap, 5,000 subsamples)

Indirect Path	$\beta_{indirect}$	SD	t	p	95% CI	β_{direct}	Type	VAF
Panel A: PSP as Intervening construct								
FSP → PSP → PPC	**0.210**	0.048	4.381	**<0.001**	[0.121, 0.308]	–	Indirect-only	1.00
FSP → PSP → SS	**0.179**	0.052	3.413	**0.001**	[0.082, 0.284]	–	Indirect-only	0.79
AUT → PSP → SS	**0.070**	0.031	2.243	**0.025**	[0.012, 0.133]	–	Indirect-only	0.58
AUT → PSP → PPC	**0.083**	0.036	2.292	**0.022**	[0.016, 0.157]	–	Indirect-only	1.00
Panel B: PPC as Intervening construct								
PSP → PPC → EMP	**0.154**	0.043	3.587	**<0.001**	[0.076, 0.243]	–	Indirect-only	0.63
PSP → PPC → IWP	**0.146**	0.045	3.275	**0.001**	[0.063, 0.238]	–	Indirect-only	0.75
PSP → PPC → EMP → SS	**0.041**	0.021	1.988	**0.047**	[0.002, 0.084]	–	Indirect-only	0.49
JSR → PPC → EMP	**0.115**	0.040	2.871	**0.004**	[0.041, 0.197]	–	Indirect-only	0.43

Indirect Path	$\beta_{indirect}$	SD	t	p	95% CI	β_{direct}	Type	VAF
JSR → PPC → IWP	**0.109**	0.046	2.378	**0.017**	[0.024, 0.203]	–	Indirect-only	0.33
JSR → PPC → EMP → SS	**0.031**	0.015	2.003	**0.045**	[0.002, 0.062]	–	Indirect-only	0.21
CSR → PPC → EMP	**0.106**	0.035	3.004	**0.003**	[0.041, 0.178]	–	Indirect-only	0.59
CSR → PPC → IWP	**0.101**	0.040	2.531	**0.011**	[0.027, 0.183]	–	Indirect-only	0.87
CSR → PPC → EMP → SS	**0.028**	0.014	2.032	**0.042**	[0.003, 0.058]	–	Indirect-only	0.49
PPC → EMP → SS	**0.114**	0.044	2.590	**0.010**	[0.032, 0.204]	–	Indirect-only	0.56
Panel C: ENG as Intervening construct								
AUT → ENG → IWP	**0.072**	0.033	2.201	**0.028**	[0.011, 0.140]	–	Indirect-only	0.62
JSR → ENG → IWP	**0.209**	0.054	3.855	**<0.001**	[0.108, 0.319]	–	Indirect-only	0.63
Panel D: IWP and EMP as Downstream Transmitters								
ENG → IWP → EMP	**0.184**	0.047	3.944	**<0.001**	[0.097, 0.280]	–	Indirect-only	1.00
PPC → IWP → EMP	**0.186**	0.049	3.829	**<0.001**	[0.096, 0.286]	0.642	Complementary*	0.22
IWP → EMP → SS	**0.122**	0.048	2.568	**0.010**	[0.033, 0.220]	–	Indirect-only	1.00
ENG → IWP → EMP → SS	**0.049**	0.024	2.044	**0.041**	[0.005, 0.099]	–	Indirect-only	0.80
PPC → IWP → EMP → SS	**0.050**	0.020	2.522	**0.012**	[0.015, 0.092]	–	Indirect-only	0.25

* β_indirect = standardised specific indirect effect; SD = bootstrap standard deviation; t = β/SD; p = bootstrap p-value; 95% CI = bias-corrected and accelerated bootstrap confidence interval based on 5,000 resamples; β_direct = standardised direct effect from the antecedent to the outcome (where present in the model); VAF = share of the total effect carried through the intervening construct (β_indirect / β_total). Cells in **green** indicate an indirect-effect estimate

whose 95% BCa interval excludes zero. The "Type" classification has been removed from the table because no mediation hypothesis is advanced; the values are reported descriptively.

Multi-Segment (Serial) Specific Indirect Effects

Table 5-18 reports the significant multi-segment specific indirect effects, that is, chains in which the effect of an antecedent on an outcome passes through two or more sequential intervening constructs. These chains are descriptive consequences of the directly hypothesised paths (H1, H2a, H3a, H3b, H6, H7a, H7b, H8a, H8b, H9b): a multi-segment indirect effect can only be non-zero if every direct path it traverses is itself supported.

Table 5-18 Multi-segment specific indirect effects (significant chains only; bootstrap, 5,000 subsamples)

Serial Indirect Path	β	SD	t	p	Sig.
FSP Chains (via PSP → PPC)					
FSP → PSP → PPC → IWP	**0.085**	0.025	3.350	**0.001**	**
FSP → PSP → PPC → EMP	**0.090**	0.025	3.628	**<0.001**	***
FSP → PSP → PPC → IWP → EMP	**0.039**	0.012	3.187	**0.001**	**
FSP → PSP → PPC → EMP → SS	**0.024**	0.012	2.018	**0.044**	*
FSP → PSP → PPC → IWP → EMP → SS	**0.010**	0.005	2.163	**0.031**	*
AUT Chains (via PSP → PPC)					
AUT → PSP → PPC → IWP	**0.034**	0.017	2.023	**0.043**	*
AUT → PSP → PPC → EMP	**0.035**	0.017	2.086	**0.037**	*
AUT → PSP → PPC → IWP → EMP	**0.015**	0.008	2.017	**0.044**	*
AUT Chains (via ENG)					
AUT → ENG → IWP → EMP	**0.033**	0.016	2.003	**0.045**	*
JSR Chains (via PPC)					
JSR → PPC → IWP → EMP	**0.050**	0.023	2.199	**0.028**	*
JSR Chains (via ENG)					
JSR → ENG → IWP → EMP	**0.096**	0.031	3.060	**0.002**	**

Serial Indirect Path	β	SD	t	p	Sig.
CSR Chains (via PPC)					
CSR → PPC → IWP → EMP	**0.046**	0.020	2.347	**0.019**	*
Downstream Chains					
PSP → PPC → IWP → EMP	**0.067**	0.021	3.153	**0.002**	**
PSP → PPC → IWP → EMP → SS	**0.018**	0.008	2.132	**0.033**	*

Note: Only chains with $p < 0.05$ are listed. The complete table of all multi-segment indirect effects is provided in Appendix D.12. The longest significant chain, FSP → PSP → PPC → IWP → EMP → SS ($\beta = 0.010$, $p = 0.031$), traces the model's full sequence and is reported for completeness; its small magnitude is the expected consequence of multiplicative attenuation across five segments.

Construct-Level Summary of Indirect Transmission

Table 5.19 consolidates the two- and multi-segment results by intervening construct. It reports, for each of PSP, PPC, and ENG, the antecedents whose total effect is decomposed through it and the outcomes that are reached.

Table 5-19 Summary of indirect transmission paths through each intermediate construct

Intervening construct	Antecedents Transmitted	Outcomes Reached	Sig. Paths	VAF range
PSP	FSP, AUT	PPC, SS, and (via PPC) IWP, EMP	4 simple + 8 serial	0.58 - 1.00
PPC	PSP, JSR, CSR	IWP, EMP, SS (via EMP)	9 simple + 7 serial	0.21 - 0.87
ENG	AUT, JSR	IWP, and (via IWP) EMP	2 simple + 3 serial	0.62 - 0.63

Note: "Sig. indirect paths" counts specific indirect effects with 95% BCa intervals excluding zero. VAF is reported as the range across the antecedent–outcome combinations channelled through that construct. The table is descriptive: it summarises the magnitude of indirect transmission inherent in the directly hypothesised paths (H1–H9b) and does not test additional hypotheses.

Total Effects: Direct and Indirect Components

Table 5.20 decomposes each total antecedent-to-outcome effect estimated in the structural model into its direct component (where the model specifies one) and the sum of its indirect components. Because no antecedent (FSP, AUT, JSR) is connected to an outcome (IWP, EMP, SS) by a direct path in the structural model, the entire total effect of those antecedents is, by design, carried indirectly; "% indirect" therefore reads as 100% in those rows. Where a direct path is specified, H5b (CSR → IWP) and H8a (PPC → EMP), the table reports both the direct and the indirect components.

Table 5-20 Total Effects Decomposition: Antecedents to Outcomes

Antecedent → Outcome	Total Effect	t	P	Direct	Indirect	% Indirect
Flow Stability Perception (FSP)						
FSP → IWP	**0.114**	4.133	**<0.001**	–	0.114	100%
FSP → EMP	**0.142**	4.651	**<0.001**	–	0.142	100%
FSP → SS	**0.228**	4.663	**<0.001**	–	0.228	100%
FSP → PPC	**0.210**	4.381	**<0.001**	–	0.210	100%
Perceived Autonomy (AUT)						
AUT → IWP	**0.117**	2.999	**0.003**	–	0.117	100%
AUT → EMP	**0.089**	2.971	**0.003**	–	0.089	100%
AUT → SS	**0.121**	3.170	**0.002**	–	0.121	100%
AUT → PPC	**0.083**	2.292	**0.022**	–	0.083	100%
Job Stress Reduction (JSR)						
JSR → IWP	**0.334**	5.014	**<0.001**	–	0.334	100%
JSR → EMP	**0.268**	4.040	**<0.001**	–	0.268	100%
JSR → SS	**0.145**	2.586	**0.010**	–	0.145	100%
Comparative Superiority (CSR)						
CSR → IWP	**0.116**	2.751	**0.006**	H5b direct	0.101 (via PPC)	87%
CSR → EMP	**0.179**	3.214	**0.001**	–	0.179	100%

Antecedent → Outcome	Total Effect	t	P	Direct	Indirect	% Indirect
CSR → SS	**0.057**	2.373	**0.018**	–	0.057	100%
Intervening Construct-Level Total Effects						
PSP → IWP	**0.195**	4.223	**<0.001**	–	0.195	100%
PSP → EMP	**0.243**	4.711	**<0.001**	–	0.243	100%
PPC → EMP	**0.214**	4.488	**<0.001**	H8a direct	0.186 (via IWP)	87%
PPC → SS*	**0.203**	3.634	**<0.001**	–	0.203	100%
ENG → EMP	**0.184**	3.944	**<0.001**	–	0.184	100%

Note: SmartPLS 4 Total Effects output (Appendix D.11). "–" in Direct column indicates no direct path exists in the structural model; the entire total effect is carried indirectly through intervening constructs. % Indirect = indirect effect / total effect × 100. Total effects from PPC and ENG to SS aggregate the contributions of all indirect chains identified in Tables 5.19 and 5.20. The "Direct" column is "–" where no direct structural path exists in the model

5.3.5 Robustness and Predictive-Validity Recap

Three sets of checks confirm the stability of the Study 2 estimates. First, the measurement-model evidence reported in Section 5.3.2 satisfied every reliability, convergent-validity, and discriminant-validity criterion specified in the methodology, including the formative-construct criteria for Flow Stability Perception and Comparative Superiority. Second, the structural-model estimates reported in Tables 5.14 - 5.18 are bootstrap-robust: every direct path remains significant under 5,000 bias-corrected resamples, and every indirect effect reported as significant is supported by a 95% bootstrap confidence interval that excludes zero. Third, the predictive-validity diagnostics reported in Table 5.15 confirm that the model's explanatory power is not confined to the estimation sample: every endogenous construct returns a positive Q^2, and all six values exceed the 0.35 threshold for large predictive relevance. The Study 2 evidence base is therefore stable across the three diagnostic dimensions specified in the analytical protocol of Section 3.8 of the methodology.

5.3.6 Boundary-Condition (Moderation) Tests

The structural model also tested eight boundary-condition (moderation) hypotheses (S2-H10 through S2-H17) examining whether selected operator and operational

characteristics moderate the strength of specific structural paths. The seven moderator constructs - Passenger Type, Interaction Frequency, Level of Responsibility, Years of Experience, Operational Area, Role, and Flights per Shift - and the eight interaction terms used to test these hypotheses follow the single-indicator formative specification reported in Tables 5.21 and 5.22. The interaction effects themselves were estimated through the two-stage PLS-SEM approach recommended for single-indicator formative moderators (Henseler, Ringle and Sarstedt, 2015; Hair et al., 2022), with significance evaluated through 5,000 bootstrap resamples. Table 5.23 reports the eight interaction-effect tests.

Table 5-21 Single-Indicator Moderator Constructs

Construct (moderator)	Indicator	Weight	VIF	t-statistic
Role	Q12	1.000	1.000	n/a
Years of Experience	Q13	1.000	1.000	n/a
Interaction Frequency	Q14	1.000	1.000	n/a
Flights per Shift	Q15	1.000	1.000	n/a
Level of Responsibility	Q16	1.000	1.000	n/a
Operational Area / Terminal	Q17	1.000	1.000	n/a
Primary Passenger Type	Q18	1.000	1.000	n/a

Note: Single-indicator constructs carry the variance of their single observed measure exactly. SmartPLS implements this by fixing the indicator loading at 1.000 and producing VIF values of 1.000 with no bootstrap t-statistic, which is standard PLS-SEM practice for identity constructs (Hair et al., 2022).

Table 5-22 Interaction Terms as Single-Indicator Formative Constructs

Interaction term	Indicator	Weight	VIF	t-statistic
Flights per Shift × IWP	FlightsPerShift × IWP	1.000	1.000	n/a
Interaction Frequency × PPC	InteractionFrequency × PPC	1.000	1.000	n/a
Level of Responsibility × PPC	Responsibility × PPC	1.000	1.000	n/a
Level of Responsibility × EMP	Responsibility × EMP	1.000	1.000	n/a

Table 5-22 Interaction Terms as Single-Indicator Formative Constructs

Interaction term	Indicator	Weight	VIF	t-statistic
Operational Area × EMP	Area × EMP	1.000	1.000	n/a
Role × PPC	Role × PPC	1.000	1.000	n/a
Passenger Type × FSP	PassengerType × FSP	1.000	1.000	n/a
Years of Experience × IWP	Experience × IWP	1.000	1.000	n/a

Table 5-23 Moderation Hypotheses

H	Interaction Path	B	SE	T	Decision
S2-H10	PassType × (FSP→PSP)	0.003	0.017	0.176	Not supported
S2-H11	IntFreq × (PPC→EMP)	−0.012	0.018	0.667	Not supported
S2-H12	Resp × (PPC→EMP)	0.001	0.022	0.045	Not supported
S2-H13	YrsExp × (IWP→EMP)	0.000	0.000	n/a	Not supported
S2-H14	**Area × (EMP→SS)**	**−0.059**	**0.030**	**1.967**	**Supported***
S2-H15	**Role × (PPC→EMP)**	**0.082**	**0.021**	**1.980**	**Supported***
S2-H16	Exp × (PPC→EMP)	−0.020	0.019	1.052	Not supported
S2-H17	Flights × (IWP→EMP)	0.001	0.022	0.045	Not supported

5.4 CONSOLIDATED HYPOTHESIS DECISIONS

Across the two studies, thirty-three hypotheses were tested: eight directional tests in Study 1 (S1-H1 through S1-H6b), seventeen direct effects in Study 2 (S2-H1 through S2-H9b), and eight boundary-condition (moderation) tests in Study 2 (S2-H10 through S2-H17). Twenty-seven of the thirty-three hypotheses were supported, yielding an overall support rate of 82%. All operational and direct-effect hypotheses were supported (eight out of eight in Study 1; seventeen out of seventeen direct effects in Study 2); two of the eight

boundary-condition hypotheses reached significance, and six did not. Table 5.24 reports the consolidated decision summary.

Table 5-24 Consolidated Hypothesis Decisions Across Both Studies

Study	Hypotheses tested	Supported	Not supported	Support rate
Study 1 - Field experiment	8 directional tests (S1-H1 - S1-H6b)	8	0	100%
Study 2 - Direct effects	17 (S2-H1 - S2-H9b)	17	0	100%
Study 2 - Boundary conditions (moderation)	8 (S2-H10 - S2-H17)	2	6	25%
Total	**33**	**27**	**6**	**82%**

5.5 CHAPTER SUMMARY

This chapter has reported the empirical findings of the research programme in two evidential streams. Study 1 produced the operational evidence: across 171 flights stratified into a fully crossed 48-cell design, the rtBRMS treatment was associated with covariate-adjusted reductions in Gate Occupation Time of approximately twelve to thirteen minutes, with significant compression of the boarding window (approximately 4.05 minutes) and the deboarding window (approximately 1.98 minutes), and with phase-specific throughput uplifts of approximately 1.6 to 1.7 passengers per minute. The Gate Occupation Time effect amplified at gates of greater architectural complexity and held across all four passenger-load quartiles and all temporal bands, and the rtBRMS treatment increased the probability of meeting the FastBoard and FastDeboard high-performance thresholds. The robustness, sensitivity, and diagnostic checks reported in Section 5.2.3 confirm that these effects are not artefacts of a particular distributional assumption or estimator.

Study 2 produced the operator user-experience evidence. The measurement model satisfied every reliability, convergent-validity, and discriminant-validity criterion across all ten constructs, with the two formative composites confirmed through the indicator-

collinearity, outer-weight-significance, and outer-loading-relevance protocol. The structural model estimated through PLS-SEM with 5,000 bootstrap resamples returned significance for every one of the seventeen direct paths, with R^2 values for the endogenous constructs ranging from 0.486 to 0.662 and Q^2 values that all exceed the 0.35 large-predictive-relevance threshold. The decomposition of total effects returned nineteen significant two-segment indirect effects and fourteen significant multi-segment indirect chains, including the complete five-segment chain from Flow Stability Perception through Perceived System Predictability, Perceived Performance Contribution, Individual Work Performance, and Employee Productivity to System Satisfaction. The eight boundary-condition (moderation) tests returned two significant interactions (Operational Area × EMP → SS; Role × PPC → EMP) and six non-significant ones, yielding a Study 2 boundary-condition support rate of 25% (two of eight) alongside the 100% support rate for the seventeen direct-effect tests.

The substantive interpretation of these findings - what they imply for queueing theory and the Theory of Constraints, for the Job Demands-Resources model, for the Technology Acceptance literature, for human-automation interaction theory, and for the Information Systems Success literature, and where they converge with, extend, or diverge from prior empirical work on boarding and turnaround management - is reserved for Chapter 6. The contributions, recommendations for practice, and reflections on what the research process has taught me are reserved for Chapter 7.

6. DISCUSSION

6.1 OVERVIEW OF THE CHAPTER

Chapter 5 reported, in descriptive form, what the data of the two studies show. The task of this chapter is to read those findings against the literature and to draw out their wider meaning. Two evidential streams - the field-causal evidence of Study 1 and the operator user-experience evidence of Study 2 - are now situated within the academic conversations they speak to: the operations-research tradition on boarding and turnaround management, the queueing-theoretic tradition that explains why variance suppression near saturation matters disproportionately, the human-factors tradition on operator response to automation, and the organisational and information-systems traditions that explain how operators internalise and act on a stabilised flow regime. The thesis sits at the intersection of these traditions, and a discussion has to do justice to all of them.

The chapter advances along five threads. Section 6.2 interprets the operational findings of Study 1 within queueing theory and the Theory of Constraints, with explicit comparison against the simulation-based boarding literature (Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015; Moreira et al., 2023) and the more recent process-mining and machine-learning evidence (Rott, Schultz and Fricke, 2023; Gehlen and Ronzani, 2025). Section 6.3 turns to the operator user-experience mechanism of Study 2, beginning with the cognitive fulcrum identified by the structural model and reading it against the human-automation interaction literature (Lee and See, 2004; Wickens et al., 2015; Endsley, 2017). The remaining sections - the belief-to-performance pathway and the framework triangulation across Job Demands-Resources, Technology Acceptance, and Information Systems Success; the systematic comparative reading against prior empirical work; the integrated socio-technical synthesis of both studies; the limitations qualifying interpretive reach; and the chapter summary - are continued in Part 2 (*ch6-discussion-2.html*) so that each file remains comfortably openable.

Two theoretical anchors give the discussion analytical precision. The first is the heavy-traffic regime of Kingman's (1961, 1962) approximation, in which expected waiting time in a G/G/1 queue near saturation scales with the sum of squared coefficients of

variation of arrival and service processes, divided by twice the complement of utilisation. At the 0.85 to 0.90 utilisations characteristic of peak boarding banks, even modest reductions in arrival-side variance are predicted to yield disproportionately large contractions in waiting time and in the phase durations that form the turnaround critical path. The second anchor is Little's (1961, 2011) law, which relates work-in-process, throughput, and cycle time independently of distributional assumptions and predicts that capping work-in-process at chokepoints while lifting sustainable rate forces cycle time to contract. The two anchors are complementary: Kingman explains why variance reduction at high utilisation produces outsized returns; Little explains why the resulting cycle-time contraction is structurally guaranteed rather than empirically contingent. The A-CDM literature, in turn, has framed predictability as an information problem to be solved by disciplined milestone exchange across partners (Schultz, 2018); the present thesis recasts it as a flow-control problem in which reliable estimates require a stabilised underlying process. The dual-study design knits these positions together: the controller produces a more regular signal at the stand, operators turn that signal into anticipation and coordinated action, and the network interface receives more accurate, more actionable estimates.

6.2 STUDY 1: THE OPERATIONAL MECHANISM IN THEORETICAL PERSPECTIVE

Study 1 addresses a gap in the airport-operations literature that is at once empirical and conceptual. Empirically, no prior work has provided field-causal evidence on whether real-time, rule-based passenger-flow control can improve turnaround performance under authentic operational heterogeneity. Conceptually, the literature has been dominated by a sequencing paradigm that treats the boarding process as a problem of choosing the right order in which passengers should enter the cabin, rather than as a flow-control problem of governing the rate, variability, and spatial distribution of passenger movement in real time. The distinction matters because sequencing solutions, however elegant in simulation, are routinely overwhelmed by the stochastic realities of live operations - late arrivals, carry-on congestion, families that cannot be separated, and the irreducible heterogeneity of passenger behaviour (Steffen and Hotchkiss, 2012; Schultz, 2018). The findings reported in Chapter 5, read through queueing theory and the Theory of Constraints, show that

reducing arrival variability and capping work-in-process at chokepoints produces systemic benefits that extend beyond any single phase (Little, 1961; Kingman, 1961). The system does not merely speed up boarding; it changes the statistical character of the entire turnaround by suppressing the variance that drives non-linear deterioration under load. This is a qualitatively different claim from the one made by simulation studies of structured boarding, which typically report mean time savings without addressing the distributional properties that determine reliability and milestone predictability.

6.2.1 Reframing Turnaround Management as a Flow-Execution Problem

The central conceptual contribution of Study 1 is a reframing of turnaround management itself. Where the dominant simulation literature has asked "what is the optimal boarding sequence?" (Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015; Moreira et al., 2023), the present field evidence asks a different question: what happens when the rate and routing of passenger movement are governed in real time? The answer is that the system moves from a regime characterised by high variance, frequent threshold violations, and reactive recovery to one characterised by compressed distributions, stable rates, and proactive governance. The contribution is therefore not a marginal improvement on existing optimisation but a different framing of what kind of problem turnaround performance actually is.

Theoretical thread

Boarding research has been a sequencing literature looking for a sequencing solution. The evidence here suggests it should have been a flow-control literature looking for a variance-suppression solution. The two are not interchangeable: sequencing operates on the order of arrivals while leaving their rate and variability unconstrained, whereas flow control operates directly on the variance term in the queue. Kingman's approximation predicts that the second is the dominant lever at the utilizations characteristic of peak boarding, and the field evidence is consistent with that prediction.

The boarding-window compression observed in Chapter 5 sits at the upper end of the magnitudes reported in the simulation literature. Steffen and Hotchkiss (2012)

recovered three to four minutes in mock-fuselage trials with optimised seat sequences and seventy-two compliant participants; Schultz (2018) reported reductions of ten to twenty per cent through outside-in and window-first strategies under stochastic agent-based simulation; Jaehn and Neumann (2015) and Moreira et al. (2023) reported two- to four-minute reductions under similar policy assumptions. The convergence with the present field evidence is directional but the magnitude is striking: the field intervention recovers, in live operations and without any compliance assumptions, what these simulations recovered only by stipulating that passengers obey seat-specific orders. The proper reading is not that prior simulation work overstated benefits; it is that the field results suggest such work was optimising the wrong lever. Structured sequencing recovers boarding time only when arrivals are dispersed, while the flow controller in the present study produces dispersed arrivals as a precondition rather than as an assumption (Steffen and Hotchkiss, 2012; Schultz, 2018).

The whole-turnaround Gate Occupation Time effect has no direct precedent in the boarding-optimisation literature, because no prior study has quantified the whole-turnaround consequence of phase-level variance suppression under field conditions. The closest comparison is Evler et al. (2022), who demonstrated that turnaround-level interventions produce network-level savings exceeding the sum of phase-specific improvements. The present finding is the field-causal counterpart to that compounding logic, with the variance-propagation mechanism formalised in Hopp and Spearman's (2011) factory-physics framework operating across the full turnaround sequence rather than within boarding alone. In other words, what looks at the phase level like a four-minute saving on boarding propagates through the rest of the turn as additional minutes saved on cleaning overlap, ramp coordination, and pushback preparation - not because the controller acts on those activities directly, but because it removes the variance that would otherwise destabilise their start times. The analogy with manufacturing is exact: in factory-physics terms, eliminating variance at one station amplifies the smoothing effect at every downstream station, and the phase-level improvement is therefore a structural understatement of the system-level gain (Hopp and Spearman, 2011).

6.2.2 Three Portable Design Principles for Flow Execution

The empirical evidence converges on three portable design principles that jointly explain why some boarding interventions stabilise turnarounds while others fail. These principles are grounded in classical queueing theory and the Theory of Constraints, and they operate as an interdependent system rather than as isolated rules. Implementing any one principle in isolation is likely to produce disappointing results, because the mechanisms they address are coupled: pacing without topology awareness creates bottlenecks at shared nodes; topology awareness without pacing allows burst arrivals to overwhelm even well-designed routing; and both are futile if milestones are treated as exogenous targets rather than as emergent properties of stabilised queues.

The first principle is that pacing must precede policy. Stabilising the inflow of passengers and explicitly capping work-in-process at the aircraft door and within the aisle is a necessary precondition for effective control. In line with Little's law and Kingman's approximation, uncontrolled arrival streams amplify variability and propagate burstiness downstream, overwhelming local policies regardless of their logical soundness. Policies that govern sequence or priority without an upstream pacing mechanism consistently introduce stochastic surges, leading to aisle congestion and door interference rather than throughput gains (Little, 1961; Kingman, 1961). This principle has a direct analogue in manufacturing: the Toyota Production System's insistence on heijunka, production levelling, before kanban, pull signalling, reflects the same insight that one cannot pull smoothly from an unlevelled source (Hopp and Spearman, 2020). The implication for airport-operations research is that the substantial body of work on optimal boarding strategies is not so much wrong as conditional - it presupposes a pacing regime that the present evidence shows must be produced rather than assumed.

The second principle is that effective flow execution requires topology-aware routing. Routing rules must be sensitive to the geometry of shared spaces - particularly door thresholds, aisle intersections, and overhead-bin access zones - where multiple passenger streams compete for the same physical resources. When routing logic ignores

these shared constraints, cross-stream interference and transient deadlocks emerge even under otherwise disciplined boarding sequences. Rules that adapt dynamically to spatial topology reduce blocking probabilities and preserve flow continuity across heterogeneous cabin layouts. The literature on slot allocation under shared-access constraints (Pellegrini, Castelli and Pesenti, 2017) has theorised the non-linear scaling of coordination demand with architectural complexity but has not previously been able to demonstrate empirically that a flow-control intervention produces correspondingly amplified benefits at complex configurations. The interaction effect for S1-H4 reported in Chapter 5 supplies precisely that empirical bridge. Rott, Schultz and Fricke (2023) had documented through process mining that turnaround variability is concentrated at architecturally complex configurations, but had not been able to evaluate intervention effects differentially across gate types. The present interaction is, on the available evidence, the first empirical demonstration that the benefits of real-time flow control scale with architectural complexity in the way the prior theoretical work predicted. The significance extends beyond aviation: any service system with shared physical infrastructure - hospital corridors, warehouse aisles, event venues - faces analogous interference dynamics, and the principle of topology-aware routing applies with equal force.

The third principle is that milestones should be governed as constraints rather than monitored as timestamps. Operational markers such as start-boarding, ready, and TOBT function effectively only when treated as outputs of stabilised queues, not as independent targets to be achieved through managerial escalation. Consistent with the Theory of Constraints, these milestones reflect the state of the system's binding constraint and cannot be reliably advanced without first stabilising the upstream flow feeding that constraint. Treating milestones as exogenous control variables obscures causal structure and incentivises local optimisation, whereas constraint-based governance aligns operational control with system-level throughput (Schultz and Reitmann, 2018). This insight has direct implications for A-CDM governance: the current emphasis on milestone accuracy as an information-sharing problem should be complemented by an emphasis on milestone reliability as a flow-control problem. A-CDM has framed predictability as an information problem to be solved through disciplined milestone exchange across partners; the present

evidence reframes it as a flow-control problem, in that no estimate can be accurate if the underlying process is stochastic and uncontrolled. The two framings are complementary rather than competing - A-CDM specifies what to share between partners; the present controller specifies what to stabilise so that shared estimates become reliable.

6.2.3 Where the Operational Mechanism Matters Most

The boundary-condition tests reported in Chapter 5 - the gate-complexity interaction (S1-H4) and the load-quartile robustness analysis (S1-H5) - locate the operational mechanism within the regimes in which it matters most. The load-moderation pattern is consistent with the heavy-traffic regime of Kingman's approximation: variance-reduction interventions yield disproportionately larger benefits as utilisation approaches capacity. Pyrgiotis et al. (2013) demonstrated this network-level non-linearity in delay propagation; the present finding locates the mechanism at the stand, where the variance is born and where the intervention can act. The consistency of the rtBRMS effect across temporal bands further indicates that the controller's effectiveness is not contingent on a particular operational regime but holds under the full range of conditions the airport encountered during the study window. The combined reading of S1-H4 and S1-H5 against the queueing literature is therefore that the mechanism does what theory predicts in the regimes where theory predicts the largest returns, and that it remains stable in the regimes where the theory does not predict differential returns. Both patterns are consistent with the underlying logic; neither is consistent with a chance pattern in the data.

6.2.4 The S1-H6b Logistic-Regression Diagnostic Pattern in Theoretical Context

One feature of the Study 1 logistic-regression output deserves explicit comment in the discussion, because its interpretation is consequential for how the FastDeboard finding (S1-H6b) is read. The coefficient correlation matrix reported in Table 5.8 shows several pairs with correlations exceeding the conventional warning threshold of $|r| \geq 0.90$. As Chapter 5 makes clear, these are correlations between the instabilities of coefficient estimates rather than between raw variables, and they arise from structural dependencies that are inherent to logistic regression with multiple dummy-coded categorical predictors. The intercept absorbs the reference-category means for all categorical variables

simultaneously, which mechanically correlates its estimate with every dummy indicator; and when two sets of dummies partition the same underlying operational dimension - as Gate_Type and Shared_Access_Points do, because shared access points are a direct physical consequence of gate topology - their coefficient estimates are necessarily correlated. The substantive implication for the discussion is that the FastDeboard finding cannot be dismissed on the grounds that Table 5.8 contains values close to one. The Variance Inflation Factor diagnostics reported in Appendix D.4 confirm that the predictor space itself is well behaved, and the Firth-penalised maximum-likelihood estimator (Firth, 1993) absorbs the residual instability that the dummy-coded design induces. The likelihood-ratio test, the classification accuracy, and the predicted probabilities are therefore valid; the high coefficient correlations reflect the geometry of the design rather than a problem with the inference. This reading is consistent with the standard treatment of separation in categorical regression (Hosmer, Lemeshow and Sturdivant, 2013; King and Zeng, 2001) and confirms that the FastDeboard threshold finding belongs to the same evidential class as the continuous-outcome findings reported in the GLMs.

6.3 STUDY 2: THE USER-EXPERIENCE MECHANISM IN THEORETICAL PERSPECTIVE

Study 2 addresses a gap that is, in some respects, more consequential than the operational gap closed by Study 1. While it is valuable to know that the controller reduces Gate Occupation Time and lifts phase-specific throughput, those numbers are inert unless the people who operate the system recognise, internalise, and act on the stabilised flow that produces them. The history of technology implementation in complex service environments is filled with systems that delivered measurable performance improvements in controlled conditions but failed to sustain those improvements because operators did not understand, predict, or engage with the technology in their daily work (Venkatesh and Davis, 2000). Study 2 was designed precisely to prevent the present thesis from making the same mistake: it tests whether the operational mechanism documented in Study 1 has an operator user-experience counterpart strong enough, stable enough, and actionable enough to sustain the operational gains in practice. The central question for the discussion is therefore not whether the structural paths are statistically significant - Chapter 5 has

already established that they are - but what the pattern of those paths means when read against the literature on operator response to automation, against the Job Demands-Resources framework, and against the established theories of technology acceptance and information-systems success.

The estimated structural model exhibits an internally coherent pattern that the discussion will trace from antecedent to outcome. Flow stability perception exerts a strong positive influence on perceived system predictability; predictability in turn lifts perceived performance contribution and engagement, and contributes directly to system satisfaction; perceived autonomy promotes both predictability and engagement; job stress reduction elevates contribution and engagement; perceived performance contribution reinforces engagement; and perceived performance contribution and engagement jointly improve individual work performance, with perceived performance contribution feeding into employee productivity. This is, viewed schematically, a cascade from stability to predictability, onward to usefulness-type appraisals and motivation, and finally to performance, productivity, and satisfaction. The substantive significance of the cascade lies not in the individual paths - significance is reported in Chapter 5 - but in how the pattern reads against three established theoretical frameworks that the empirical literature has typically treated as alternatives. The remainder of Section 6.3 develops that reading.

6.3.1 Stability as the Cognitive Fulcrum

The strongest single relationship in the structural model is the path from flow stability perception to perceived system predictability (S2-H1). This relationship is theoretically central rather than a numerically convenient artefact of the model specification, and reading it against the human-automation interaction literature requires care. In that literature, predictability is understood as one of three pillars of operator reliance on automation, alongside dependability and faith (Lee and See, 2004), and the predictability-formation pathway has been studied across two decades of human-factors research. What stands out in the present model is not the existence of the pathway, which is well established, but its magnitude. The relationship is substantially stronger here than the predictability-formation paths typically reported in the human-automation literature,

where Wickens et al. (2015) and Endsley (2017) place the corresponding effects in the medium range across a wide variety of automated systems. The most plausible reading of this difference, given the consistency of the broader literature, is that flow stability at the gate is a continuously observable physical phenomenon that supplies rich, redundant evidence for predictability judgements. In many automation contexts the system's behaviour is partially opaque - the automation's logic must be inferred from indirect signals, error messages, and the absence of overt intervention - which bounds the strength of the predictability-formation pathway from above. At the gate, by contrast, the rhythm of passenger movement is itself the observable behaviour of the controller, and operators have access to the same user-experience cues regardless of role or expertise. The implication is that the Lee and See framework holds, but its predictions about the magnitude of the predictability pathway are conditional on the user-experience accessibility of the system's behaviour - a contextual sensitivity the framework anticipates but the empirical literature has rarely been positioned to test.

The theoretical significance of this finding extends beyond the immediate context. In cognitive science, predictability is understood as the brain's capacity to generate forward models of environmental states, reducing the computational cost of real-time decision-making by allowing pre-compiled action plans to be deployed rather than constructed de novo in each situation (Clark, 2013). In operational terms, when flow looks, feels, and remains smoother and less erratic at the gate, operators can forecast what will happen next with greater confidence, and that forecasting capacity is the cognitive precondition for everything that follows in the structural model. The implication is that the controller does not merely change what happens at the gate; it changes how operators think about what happens at the gate. This cognitive restructuring is the mechanism through which operational improvements become operator user-experiencely sustainable. The reading is broadly consistent with the predictive-processing account of cognition (Clark, 2013), in which forward models are reinforced by the regular delivery of expected sensory input, and it provides a specification of the cognitive mechanism that the human-automation interaction literature has previously discussed only in general terms.

6.3.2 Antecedents of Predictability and Engagement: Three Frameworks Triangulated

From the cognitive fulcrum, the structural model opens into the antecedent layer of the operator user-experience mechanism. The pattern of paths in this layer is informative because it shows that three theoretical frameworks normally treated as competing alternatives are in fact concurrent and complementary in this operational context. The architecture in which Perceived System Predictability, Perceived Performance Contribution, and Work Engagement transmit antecedent perceptions to downstream outcomes is grounded in three converging frameworks: the Job Demands-Resources model (Bakker and Demerouti, 2007), which posits engagement as the proximal mediator between resources and performance; the Technology Acceptance Model 2 (Venkatesh and Davis, 2000), which theorises that external variables influence outcomes through perceived usefulness; and the DeLone-McLean Information Systems Success Model (DeLone and McLean, 2003), in which system quality transmits to net benefits through use and user satisfaction. The literature has typically treated these frameworks as alternatives, with researchers selecting one and bracketing the others. The present evidence shows that all three operate concurrently in the same model, with each framework's predicted pathway returning the empirical pattern its theory anticipates.

(JD-R) Job Demands-Resources (Bakker and Demerouti, 2007)

The framework predicts that resources drive performance through a motivational pathway in which engagement is the proximal mediator. The present evidence supports the framework but at the upper bound of its meta-analytic range. Christian, Garza and Slaughter's (2011) synthesis of ninety-one samples covering more than sixty thousand participants placed the resource-to-engagement effect in the medium range; the JSR-to-ENG path reported in Chapter 5 is larger. The most plausible reading is that strain reduction is more vivid in time-critical operational work than in the office and service settings that dominate the JD-R evidence base. Demerouti et al. (2001) anticipated this contextual sensitivity in the original JD-R formulation, but the empirical literature has rarely been able to test it in operationally extreme settings. The present result is one such test, and it strengthens the resource-driven branch of the model rather than challenging it.

(TAM2) Technology Acceptance Model 2 (Venkatesh and Davis, 2000)

The framework identifies output quality and result demonstrability as cognitive precursors of perceived usefulness. The finding that predictability lifts perceived performance contribution (S2-H3a) is the field-operational counterpart of that prediction: when the system's behaviour is foreseeable, its contribution becomes attributable, and attributable contribution is the cognitive condition for sustained acceptance. The substantially larger usefulness-to-net-benefits magnitude observed in the PPC-to-EMP path (S2-H8a), compared with the meta-analytic IS-Success estimates in Petter, DeLone and McLean (2008), reflects task-technology fit operating at high concentration: every system action has an immediately observable temporal consequence at the stand, so the attribution noise that diffuses the usefulness-to-performance pathway in office-based IS contexts is minimised (Goodhue and Thompson, 1995). The TAM2 framework holds, but its predictions about the magnitude of the usefulness-to-performance pathway are conditional on the task-technology fit conditions that gate operations satisfy at high concentration.

IS SuccessDeLone-McLean IS Success (DeLone and McLean, 2003)

The framework positions user satisfaction as a joint function of system quality and net benefits. The dual-channel pattern observed in Study 2 - PSP-to-SS (S2-H3c) and EMP-to-SS (S2-H9b) returning effects of comparable magnitude - is the operational realisation of that prediction. What the literature has lacked, and what the present study supplies, is field evidence that the two channels operate with comparable strength rather than with one dominating the other. Wixom and Todd's (2005) theoretical integration of user satisfaction and technology acceptance anticipated this balance but did not have the data to test it directly in an aviation-automation context.

The triangulation of these three frameworks within a single structural model is itself a substantive contribution to the literature, taken up explicitly in Chapter 7. What matters at this point in the discussion is the consistency: each framework's predicted pathway returns the empirical pattern its theory anticipates, none of the frameworks is contradicted by the data, and the magnitudes are at the upper bound of the meta-analytic range for each.

This is not a coincidence. It is, the present interpretation suggests, what one observes when an automation system is salient enough at the operator user-experience layer that the conditions all three frameworks specify - resources, attribution, and information clarity - obtain simultaneously rather than separately. The discussion of how this concurrent operation becomes visible at the level of execution and throughput is taken up in Section 6.3.4 (continued in Part 2 of this chapter).

6.3.3 Why the Operator User-Experience Mechanism Is Stable Across Operator Characteristics

The boundary-condition tests reported in Chapter 5 (Section 5.3.6) - eight moderation hypotheses examining whether selected operator and operational characteristics moderate the strength of specific structural paths - returned a largely null pattern, with two of the eight interactions reaching significance and six remaining non-significant. The substantive interpretation of this pattern is the most informative finding of Study 2 that has not appeared in the prior literature, and it requires careful reading against the human-factors tradition that the moderation tests were designed to engage. Adaptive-automation theory has emphasised that operator characteristics moderate automation acceptance (Endsley, 2017; Wickens et al., 2015), and Parasuraman and Riley (1997) argued in an influential review that reliance and acceptance vary systematically with role, expertise, and task demands.

The present evidence does not refute these positions; it bounds them. The mechanism's stability across roles, experience levels, exposure frequencies, workload bands, and passenger regimes suggests that flow stability is universally salient at the gate in a way that more abstract automation features are not. When the system's contribution is visible in the physical rhythm of passenger movement, the operator user-experience mechanism by which that visibility produces predictability and engagement is shared across operational positions, and the role-specific or expertise-specific moderation that adaptive-automation theory leads researchers to expect collapses. The two significant moderations - Operational Area on the EMP-to-SS path (S2-H14) and Role on the PPC-to-EMP path (S2-H15) - refine but do not overturn this generality. The productivity-to-

satisfaction conversion is more pronounced where throughput is operationally salient, and the contribution-to-productivity conversion is steeper in roles with greater operational leverage. Both findings are entirely consistent with the human-factors tradition; what is novel is the demonstration that they are exceptions in a setting where context-specificity has historically been the rule.

The substantive reading is therefore that context-specificity in automation acceptance is bounded by the user-experience accessibility of the system's behaviour. Where automation behaviour is opaque, role and expertise moderate operator response (Parasuraman and Riley, 1997; Endsley, 2017). Where automation behaviour is physically observable, that moderation collapses, because operators across roles share access to the same user-experience cues. This is not a refutation of context-sensitive accounts of automation acceptance but a specification of the conditions under which they apply. It also opens a productive line of future research in which operator user-experience mechanisms are compared across automation systems with varying degrees of behavioural opacity, with the prediction that the role-specific moderation pattern of Parasuraman and Riley (1997) should re-emerge as opacity increases. That research agenda is articulated in Chapter 7.

6.3.4 From Beliefs and Motivation to Execution and Throughput

The structural model does not stop at the antecedent layer. It extends into the execution layer, in which Perceived Performance Contribution and Work Engagement jointly determine Individual Work Performance, and Perceived Performance Contribution and Individual Work Performance jointly determine Employee Productivity. The pattern of paths in the execution layer is theoretically informative because it shows that contribution beliefs and motivational engagement are not redundant alternative routes to performance; they are concurrent and complementary, with each making its own incremental contribution to behaviour at the gate. This dual-route architecture is consistent with the meta-analytic evidence in the engagement literature (Christian, Garza and Slaughter, 2011), in which engagement and cognitive resources jointly predict task performance with neither subsuming the other, and it is also consistent with the dual-process accounts of behaviour change in which deliberate appraisal and affective

engagement operate on parallel channels (Strack and Deutsch, 2004). The novel element here is the specification of those parallel channels in an operational-automation context, where the empirical literature has typically modelled either the cognitive channel through Technology Acceptance variants (Venkatesh and Davis, 2000) or the motivational channel through engagement variants (Bakker and Demerouti, 2017), but has rarely modelled both within a single structural specification. The Study 2 evidence shows that doing so returns the empirical pattern that both literatures predict separately and that neither has been positioned to confirm jointly.

The interpretation of the contribution-to-productivity pathway is particularly consequential for the practical reach of the thesis. In the IS Success tradition, perceived usefulness translates to net benefits with effect sizes in the medium range across most office and service contexts (Petter, DeLone and McLean, 2008). In the present model, the corresponding magnitude is markedly larger. This is, on the most plausible reading, the empirical signature of task-technology fit operating at high concentration (Goodhue and Thompson, 1995). At the gate, every system action has an immediately observable temporal consequence: the controller stabilises arrivals, queueing dynamics shift, the stand visibly clears, and operators see the productivity outcome of their own contribution within minutes. The attribution noise that diffuses the usefulness-to-performance pathway in contexts where outcomes are delayed, distributed, or confounded with the actions of many other actors is minimised here. The reading is therefore not that the IS Success literature is wrong about the pathway's typical magnitude; it is that the pathway's magnitude is conditional on the task-technology fit conditions that gate operations satisfy at high concentration, and the empirical literature has not previously been positioned to test that conditionality directly.

The engagement-to-performance pathway carries a complementary interpretive weight. The engagement literature has consistently reported that engagement predicts task performance through a motivational channel that is conceptually distinct from cognitive appraisal (Bakker and Demerouti, 2017; Christian, Garza and Slaughter, 2011), but the field-operational evidence for this pathway has been thinner than the office-based

evidence. The present finding supplies field-operational support for the JD-R prediction in a setting where strain reduction is operationally vivid and where the resources that drive engagement - autonomy and stress reduction - are themselves products of the controller's stabilising action. The reading that the JSR-to-ENG path is at the upper bound of its meta-analytic range is therefore not surprising: the controller does not merely supply abstract resources; it supplies resources whose effect on strain and autonomy is directly perceptible at the stand. The Christian, Garza and Slaughter (2011) synthesis of ninety-one samples returned medium effect sizes for the resource-to-engagement pathway across heterogeneous contexts; the present effect, larger than that synthesis median, is consistent with the prediction the JD-R framework makes for high-strain contexts but rarely tests in field-operational settings. Field-survey evidence from contexts in which engagement is operationalised through commitment to responsibilities and willingness to exert extra effort has likewise reported that engagement outcomes are significantly associated with the perceived effectiveness of organisational interventions designed to support employee development (Menara, 2025a), reinforcing the case that the engagement-to-performance link observed in the present model is not sector-specific but reflects a generalisable feature of how operators convert motivational resources into work outcomes.

Theoretical thread

The dual-route architecture - contribution beliefs through PPC and motivational engagement through ENG, jointly producing performance - is the operator user-experience analogue of the dual-anchor architecture in Study 1, where Kingman explains why variance reduction matters disproportionately at high utilisation and Little explains why cycle-time contraction is structurally guaranteed. In each study, two complementary mechanisms operate concurrently rather than as alternatives, and the integration of the two mechanisms within a single specification is the substantive contribution.

6.3.5 Satisfaction as the Evaluative Synthesis of the Mechanism

System Satisfaction occupies the terminal position in the structural model and integrates two upstream evaluations: a direct evaluation of the system's predictability (PSP-to-SS, S2-H3c) and an indirect evaluation through productivity (EMP-to-SS, S2-H9b). The

dual-channel pattern is the operational realisation of the DeLone-McLean (2003) prediction that user satisfaction is a joint function of system quality and net benefits, and the substantive contribution lies in the comparable magnitude of the two channels. The IS Success literature has positioned satisfaction as a joint function of these two inputs but has not, on the available evidence, supplied a field-operational demonstration that the two channels operate with comparable strength rather than with one dominating the other. The Wixom and Todd (2005) integration of user satisfaction and technology acceptance anticipated this balance theoretically; the present evidence supplies the empirical confirmation in a context where both channels are experientially accessible and where the satisfaction outcome carries operational consequences for sustained use. The dual-channel pattern observed here is also consistent with prior PLS-SEM evidence from technology-intensive work environments, where satisfaction emerges as the joint product of cognitive evaluations of system reliability and attitudinal evaluations of realised job outcomes (Valaei and Rezaei, 2016).

The terminal positioning of System Satisfaction in the model also explains the relatively lower R-squared value reported in Chapter 5 ($R^2 = 0.486$). System Satisfaction is the most distal outcome in the cascade, and the operator user-experience constructs upstream are not the only determinants of satisfaction. Personal life circumstances, organisational tenure, compensation, and workplace climate all contribute residual variance to satisfaction judgements, and JD-R theory itself anticipates this dispersion (Bakker and Demerouti, 2017). The reading is therefore not that the model under-explains satisfaction; it is that satisfaction is appropriately positioned as an outcome that integrates the operator user-experience mechanism with extra-mechanism factors, and the pattern of R-squared across the model is consistent with that theoretical positioning.

6.3.6 Explanatory and Predictive Adequacy of the Structural Model

A discussion of the operator user-experience mechanism would be incomplete without an explicit reading of what the structural model's R-squared, Q-squared, and effect-size pattern means in theoretical terms, beyond their reporting role in Chapter 5. The pattern of R-squared and Q-squared values reported in Chapter 5 carries three substantive

implications for the operator user-experience mechanism. First, the two terminal performance constructs - Employee Productivity and Engagement - sit at the upper boundary of the moderate band and approach the substantial threshold; the model's antecedents account for roughly two-thirds of the between-respondent variance in how operators evaluate their own performance and engagement. This is unusually high for cross-sectional self-report data in human-automation research (Hair et al., 2022; Shmueli et al., 2019). Second, all six Q-squared values exceed the 0.35 large-predictive-relevance threshold, demonstrating that the model's explanatory power is not merely an in-sample artefact. When individual respondents are systematically held out via blindfolding, the remaining structural relationships still reconstruct the held-out indicator scores with substantial accuracy (Geisser, 1974; Stone, 1974). Third, the lowest R-squared in the model - System Satisfaction - is consistent with theoretical expectation rather than a model deficiency, for the reasons developed in Section 6.3.5.

The distinction between explanatory and predictive adequacy is particularly important for the substantive reading of these results. Shmueli (2010) drew attention to the conceptual gap between explanation and prediction in social-science modelling, arguing that strong in-sample fit does not guarantee out-of-sample predictive accuracy, and that researchers routinely confuse the two. The present model is unusual in passing both tests simultaneously: the explanatory adequacy is established by the R-squared pattern, and the predictive adequacy is established by the Q-squared pattern, with no path so weak that its removal would not reduce out-of-sample predictive accuracy. The substantive implication is that the operator user-experience mechanism is not only theoretically coherent within the sample but generalises to the prediction of held-out cases, which is the more demanding criterion for a structural model of this kind.

The effect-size pattern read jointly across β, f-squared, and q-squared answers three different questions about the same path: how strong is the standardised in-sample relationship; how much explanatory work does this predictor do for its criterion; and how much out-of-sample predictive accuracy would be lost if this predictor were dropped from the model. The strongest effects cluster on the central JD-R cascade running from

perceived stability through predictability calibration to performance: FSP to PSP returns a large effect, PPC to EMP returns a large effect, JSR to ENG returns a medium effect, and ENG to IWP returns a medium effect. Medium-to-large effects on PPC to IWP and IWP to EMP confirm that the Individual Work Performance pathway carries comparable weight to the engagement pathway, supporting the dual-route specification of the model rather than a single-channel structure. Critically, every f-squared in the table exceeds the 0.02 small-effect threshold and every q-squared is positive, indicating that no path in the model is statistically meaningful only in-sample; each predictor contributes incremental out-of-sample predictive accuracy when held out via blindfolding (Shmueli et al., 2019; Hair et al., 2022). This pattern is rare in cross-sectional structural models in the human-automation literature and warrants explicit attention in the discussion.

The measurement evidence supporting these structural conclusions is consistent and strong. The composite-reliability and convergent-validity statistics, the heterotrait-monotrait ratios, and the cross-loadings reported in Chapter 5 all sit well within accepted thresholds. The CSR formative block is well behaved. Moderator identity indicators and product terms are properly specified, and the structural results are robust to bootstrapping. Together with the explanatory and predictive adequacy results just discussed, the findings support the nomological validity of the model and its predictive utility for held-out cases. The interpretive reading of these robustness results, in turn, is that the operator user-experience mechanism is internally coherent, externally valid within the operational population the survey targets, and structurally stable enough to bear the theoretical weight Section 6.3 has placed on it.

6.4 COMPARATIVE READING: HOW THE FINDINGS BUILD ON, CHALLENGE, OR EXTEND EXISTING KNOWLEDGE

A discussion has to do more than report that findings are consistent with or different from prior work. It has to read the full set of findings against the relevant traditions in a structured way, identifying for each finding whether it is consistent with prior knowledge, extends prior knowledge, bounds the conditions under which prior knowledge applies, or is novel relative to prior empirical work. Table 6.1 supplies that systematic comparative

reading for the present thesis. Each row pairs a thesis finding with the most directly relevant prior literature and tags the relationship with one of four labels - Consistent, Extends, Bounds, or Novel - that name the form of the contribution. The table is not exhaustive of every result reported in Chapter 5; it focuses on the findings that carry interpretive weight and that the discussion has engaged with theoretically. Readers seeking a more granular, path-by-path comparison are referred to Appendix E (Comparison Matrix: Consistency of Key Findings with Prior Studies), which reports for each significant Study 2 path, indirect-effect estimate, and moderation result the standardized coefficient obtained in the present study, the typical magnitude reported in prior meta-analyses or canonical benchmark studies, the relevant theoretical lineage, and a conservatively assigned verdict (Consistent, Consistent but stronger, Novel extension, or Partially contradicts). Appendix E is intended as a transparency device that complements the synoptic reading of Table 6.1 below.

Table 6-1 Comparative reading of thesis findings against prior literature (Consistent / Extends / Bounds / Novel)

Thesis finding (Chapter 5 reference)	Most relevant prior work	Relationship	Form of the contribution
Boarding-window compression under rtBRMS (S1-H1)	Steffen and Hotchkiss (2012); Schultz (2018); Jaehn and Neumann (2015); Moreira et al. (2023)	**Extends**	Field-causal evidence reproduces the magnitudes that simulation-based sequencing has obtained only under stipulated compliance, recovered without compliance assumptions through flow control rather than sequencing.
Whole-turnaround Gate Occupation Time effect (S1-H2)	Evler et al. (2022); Hopp and Spearman (2011)	**Novel**	First field-causal demonstration that phase-level variance suppression propagates to the whole turnaround in the manner predicted by factory-physics analyses of variance propagation.
Phase-specific throughput uplift (S1-H3a, S1-H3b)	Schultz and Reitmann (2018); Rott, Schultz and Fricke (2023)	**Consistent**	Confirms theoretical predictions about phase-level rate gains under stabilised arrivals; supplies the field counterpart of process-mining evidence that variability is concentrated at architecturally complex configurations.
Gate-complexity interaction (S1-H4)	Pellegrini, Castelli and Pesenti (2017); Rott, Schultz and Fricke (2023)	**Extends**	First empirical demonstration that the benefits of real-time flow control scale with architectural complexity in the way that prior theoretical and process-mining work predicted.
Load-quartile robustness (S1-H5)	Pyrgiotis et al. (2013); Kingman (1961, 1962)	**Extends**	Field-operational calibration of the heavy-traffic regime: confirms that variance-reduction interventions yield disproportionately larger benefits as utilisation approaches capacity, in a setting where the network-level non-linearity has been theorised but not measured at the stand.

Table 6-1 Comparative reading of thesis findings against prior literature (Consistent / Extends / Bounds / Novel)

Thesis finding (Chapter 5 reference)	Most relevant prior work	Relationship	Form of the contribution
FastBoard / FastDeboard threshold attainment (S1-H6, S1-H6b)	Hosmer, Lemeshow and Sturdivant (2013); King and Zeng (2001); Firth (1993)	**Consistent**	Threshold-attainment evidence is consistent with the standard treatment of separation in categorical regression; the coefficient correlation pattern reflects the geometry of dummy-coded design rather than a problem with inference.
Flow stability to predictability path (S2-H1)	Lee and See (2004); Wickens et al. (2015); Endsley (2017); Clark (2013)	**Extends**	Returns the predictability-formation pathway at the upper bound of its expected range under conditions where the system's behaviour is experientially accessible; specifies the cognitive mechanism that the human-automation literature discusses in general terms.
Predictability to perceived performance contribution (S2-H3a)	Venkatesh and Davis (2000); Goodhue and Thompson (1995)	**Extends**	Field-operational counterpart of the TAM2 prediction that output quality drives perceived usefulness; demonstrates that the path operates with substantially larger magnitude under high task-technology fit than in office-based IS contexts.
Resource to engagement path (JSR to ENG, S2-H6c)	Bakker and Demerouti (2007, 2017); Christian, Garza and Slaughter (2011); Demerouti et al. (2001)	**Extends**	Strengthens the resource-driven branch of JD-R at the upper bound of the meta-analytic range, in a high-strain operational setting that the JD-R framework anticipated but the empirical literature has rarely been positioned to test.
Dual-channel satisfaction structure (S2-H3c, S2-H9b)	DeLone and McLean (2003); Petter, DeLone and McLean (2008); Wixom and Todd (2005)	**Extends**	Supplies field-operational confirmation that the two satisfaction channels theorised in IS Success operate with comparable strength rather than with one dominating the other.

Table 6-1 Comparative reading of thesis findings against prior literature (Consistent / Extends / Bounds / Novel)

Thesis finding (Chapter 5 reference)	Most relevant prior work	Relationship	Form of the contribution
Contribution to productivity path (PPC to EMP, S2-H8a)	Petter, DeLone and McLean (2008); Goodhue and Thompson (1995)	**Extends**	The path operates at the upper bound of the IS Success meta-analytic range; reading consistent with task-technology fit operating at high concentration in gate operations.
Bounded operator user-experience stability across roles, expertise, and exposure (six non-significant moderations)	Parasuraman and Riley (1997); Endsley (2017); Wickens et al. (2015)	**Bounds**	Bounds the adaptive-automation prediction of operator-characteristic moderation: shows that role and expertise moderation collapses when system behaviour is experientially accessible, specifying conditions under which context-sensitive accounts apply.
Operational Area moderation on EMP-to-SS (S2-H14)	DeLone and McLean (2003); Petter, DeLone and McLean (2008)	**Novel**	Productivity-to-satisfaction conversion is more pronounced where throughput is operationally salient; refines the IS Success prediction by introducing a context-salience moderator absent from the original specification.
Role moderation on PPC-to-EMP (S2-H15)	Goodhue and Thompson (1995); Bakker and Demerouti (2017)	**Novel**	Contribution-to-productivity conversion is steeper in roles with greater operational leverage, refining the task-technology fit prediction with a role-leverage moderator.

Read across the rows, Table 6.1 shows that the thesis is rarely simply consistent with or simply contradictory to prior work. The dominant relationship is one of extension and bounding: prior frameworks generally hold in the present setting, but their predictions return at the upper bound of meta-analytic ranges or under specifiable boundary conditions, and several findings are novel relative to the empirical literature without overturning the underlying theoretical positions. This reading is consistent with the expectation that a thesis advances rather than replaces existing knowledge, and it locates the thesis's substantive contribution in the conditions, magnitudes, and architectural integrations that prior work has theorised but not been positioned to test directly in field-operational aviation settings.

6.5 INTEGRATED SYNTHESIS: A SOCIO-TECHNICAL READING OF THE TWO STUDIES

The two studies of this thesis have been read separately to this point. The integrated reading that the discussion has to supply is socio-technical: the controller produces a more regular signal at the stand, operators turn that signal into anticipation and coordinated action, and the network interface receives more accurate, more actionable estimates. The signal is the same in both studies but is observed through different evidential lenses. Study 1 observes the signal at the level of physical timestamps recovered from the operations system - boarding-window minutes, Gate Occupation Time minutes, and the binary thresholds of FastBoard and FastDeboard attainment. Study 2 observes the same signal at the level of operator perception, captured through a structural model that links flow stability perception to the cognitive, motivational, and evaluative responses that operators report on validated scales. The two evidential streams converge on a coherent socio-technical mechanism: the controller stabilises arrivals, the stabilised arrivals translate into both faster turnarounds and more predictable system behaviour, the more predictable system behaviour reshapes operator cognition and motivation, and the cognitive and motivational reshaping in turn supports the sustained execution that maintains the operational gains in practice.

The synthesis is socio-technical in the strict sense that neither stream is reducible to the other. The operational gains documented in Study 1 are necessary but not sufficient: a controller that reduces Gate Occupation Time by several minutes per turn will not

produce a sustained operational change if operators do not understand what it does, do not trust its behaviour, and do not engage with it in their daily work. Conversely, the operator user-experience mechanism documented in Study 2 is necessary but not sufficient: operators who report high flow stability perception, high predictability, and high engagement on validated scales are not, by that fact alone, a sufficient cause of operational improvement; the controller has to produce the operational signal that the user-experience mechanism observes. The two studies, taken together, supply both halves of the socio-technical argument, and the integration is the substantive contribution that neither study could make alone. The socio-technical reading developed here is also consistent with broader organisational evidence that effective operational performance in multidisciplinary settings depends on the careful balancing of role differentiation, integration, and control mechanisms across professional groups working under shared operational pressures (Menara, 2025b), a balance that the gate-operations context in the present thesis reproduces in microcosm across gate agents, ramp coordinators, security personnel, and ground-handling staff.

The thesis therefore advances a socio-technical reading of turnaround flow control in which the operator user-experience mechanism is not a behavioural decoration of an essentially operational story but a structural component of the mechanism by which operational gains are produced and sustained. This reading aligns with the broader call in the operations literature for analyses that integrate physical and informational flows with the cognitive and motivational mechanisms through which operators engage with automated systems (Hopp and Spearman, 2020; Lee and See, 2004), and it positions the thesis as a contribution to that integrative literature rather than to either of its sub-traditions in isolation.

6.6 LIMITATIONS QUALIFYING INTERPRETIVE REACH

The discussion has to mark, at this point, the limitations that qualify the interpretive reach of the findings. These are limitations of interpretive reach rather than threats to the validity of the underlying evidence: the field-experimental design of Study 1 and the structural specification of Study 2 are robust to the standard threats discussed in Chapter

3, and the limitations identified here concern the breadth of theoretical conclusions that the present evidence base can support, not the soundness of the evidence within its scope.

The first limitation concerns the single-airport setting of the field experiment. The evidence reported in Chapter 5 was generated at one operational site, and the comparative reading developed in Section 6.4 has therefore engaged with the prior literature one airport at a time. The interpretive reach of the findings is bounded accordingly: the magnitudes recovered from Study 1 are field-causal evidence for the controller's effect at the site studied, and the generalisation to other airports rests on the theoretical claim that the queueing and Theory-of-Constraints mechanisms invoked in Section 6.2 are architecturally general rather than site-specific. The architectural generality of the underlying mechanisms is well established in the operations literature (Little, 1961; Kingman, 1961; Hopp and Spearman, 2011), but the empirical generalisation to multi-airport replication remains a future-research task, articulated as such in Chapter 7.

The second limitation concerns the cross-sectional nature of the operator user-experience evidence in Study 2. The structural model captures the operator user-experience mechanism at a single point in time, and the temporal ordering of the cascade from stability perception to predictability, contribution, engagement, performance, productivity, and satisfaction is theoretical rather than directly observed. The interpretive reach of Study 2 is therefore bounded by the assumption, common in cross-sectional structural modelling, that the theoretical ordering of constructs is reflected in the cross-sectional pattern of associations. The robustness checks reported in Chapter 5 - convergent validity, discriminant validity, predictive relevance under blindfolding - support the structural specification, but a longitudinal replication that observes the cascade over time is the natural next step in establishing the temporal mechanism that the cross-sectional model presupposes.

The third limitation concerns the bounded interpretation of the moderation pattern. Section 6.3.3 of Part 1 read the largely null moderation pattern as a substantive finding about the user-experience accessibility of the controller's behaviour. That reading is one of

several that the data could support. An alternative reading is that the survey instrument lacks the sensitivity to detect moderation effects that are present in the population. The two readings have different implications for future research: the first invites comparative studies across automation systems with varying degrees of behavioural opacity; the second invites psychometric refinement of the survey instrument. The discussion has favoured the first reading because the convergent and discriminant validity evidence in Chapter 5 is consistent with adequate instrument sensitivity, but the alternative is acknowledged and articulated as a future-research direction in Chapter 7.

The fourth limitation concerns the operational scope of the controller. The rtBRMS controller acts on the gate phase of the turnaround. Its effect on the network-level flow of operations is therefore mediated by the propagation mechanisms that the present evidence base does not measure directly. Section 6.5 has framed the synthesis at the stand-level scale at which the evidence was generated; the network-level extension is a theoretical possibility supported by the propagation literature (Pyrgiotis et al., 2013; Evler et al., 2022) but not directly tested by the present design. The interpretive reach of the thesis with respect to network-level claims is correspondingly bounded.

The fifth limitation concerns the operational and temporal scope of the field window. The Study 1 evidence was collected over an operational window described in Chapter 4. The interpretive reach of the findings with respect to seasonal, weather-related, and longer-cycle operational variability is bounded by that window. The robustness analyses reported in Chapter 5 against load-quartile and gate-complexity strata strengthen the case for stability across the conditions the window encountered, but the case for stability across operational regimes that the window did not encounter rests on theoretical extrapolation rather than direct evidence.

These five limitations qualify the interpretive reach of the findings without weakening the evidence within its scope. They also frame the future-research agenda articulated in Chapter 7, where each limitation maps to a corresponding research direction.

6.7 CHAPTER SUMMARY

This chapter has read the descriptive findings of Chapter 5 against the operations-research, queueing-theoretic, human-factors, organisational, and information-systems traditions that the thesis sits at the intersection of. It has interpreted Study 1 within queueing theory and the Theory of Constraints, with explicit comparison against the simulation-based boarding literature and the more recent process-mining and machine-learning evidence; it has interpreted Study 2 within the human-automation interaction literature, the Job Demands-Resources framework, the Technology Acceptance Model 2, and the Information Systems Success Model, with the three frameworks triangulated rather than treated as alternatives; it has supplied a systematic comparative reading of the findings against prior empirical work, tagging each finding's relationship to the literature as Consistent, Extends, Bounds, or Novel; it has integrated the two studies into a socio-technical reading in which the operator user-experience mechanism is a structural component of how operational gains are produced and sustained rather than a behavioural decoration of an essentially operational story; and it has marked the limitations qualifying the interpretive reach of the findings.

The substantive contributions that the discussion has established, and that Chapter 7 will summarise as the basis for the thesis's theoretical and practical claims, are five in number.

1. The reframing of turnaround management as a flow-execution problem rather than as a sequencing problem, with three portable design principles - pacing precedes policy, topology-aware routing, and milestones as constraints rather than as exogenous targets - that supply the operational logic for the reframing and locate the thesis within the wider operations and Theory-of-Constraints traditions.

2. The field calibration of Kingman's heavy-traffic regime in airport operations, supplying field-operational evidence that variance-reduction interventions yield disproportionately larger benefits as utilisation approaches capacity, in a setting where

the network-level non-linearity has been theorised but not directly measured at the stand.

3. The identification of a cognitive fulcrum at flow stability perception, with bounded context-specificity in moderation: the controller's behaviour is experientially accessible to operators across roles and expertise levels, and the role-specific moderation that adaptive-automation theory leads researchers to expect collapses under that condition, specifying the boundary condition of the human-factors prediction rather than refuting it.

4. The triangulation of the Job Demands-Resources, Technology Acceptance Model 2, and Information Systems Success frameworks within a single structural specification, in which all three frameworks return their predicted pathways at the upper bound of their meta-analytic ranges in a context where their respective conditions - resources, attribution, and information clarity - obtain simultaneously rather than separately.

5. The two-lens evaluation method, in which an operational mechanism is documented through a field-experimental design and the operator user-experience mechanism is documented through a survey-based structural model in the same operational setting, supplying both halves of a socio-technical evaluation that neither study could make alone.

These five contributions are the substantive interpretive product of the discussion. Chapter 7 turns from interpretation to consolidation, presenting the consolidated decision on each hypothesis, summarising the theoretical and practical contributions in clearly separated sub-sections, supplying a focused page of recommendations for practice, and reflecting on what has been learned through the research process.

7. CONCLUSION

7.1 OVERVIEW OF THE CHAPTER

This chapter closes the thesis in four parts. A table summarising the outcome of each of the 33 hypotheses (27 supported, 6 not supported); a focused one- to two-page section presenting the theoretical and practical contributions in two clearly separated sub-sections; a concise one-page set of recommendations for practice; and a one- to two-page reflection on what the research process taught me and how it will shape my future practice. Brief closing statement at the end.

7.2 SUMMARY OF HYPOTHESIS OUTCOMES

The two studies tested thirty-three hypotheses in total: eight directional tests in Study 1, seventeen direct effects in Study 2, and eight moderation hypotheses. Twenty-seven were supported; six were not. The complete decision summary is presented in Table 7.1 below; the underlying statistical evidence resides in Chapter 5, and the substantive interpretation in Chapter 6.

Table 7-1 Outcome of each Hypothesis

Hypothesis	Statement	Study	Outcome
S1-H1	rtBRMS reduces Gate Occupation Time	Study 1	**Supported**
S1-H2a	rtBRMS compresses the boarding window	Study 1	**Supported**
S1-H2b	rtBRMS compresses the deboarding window	Study 1	**Supported**

Table 7-1 Outcome of each Hypothesis

Hypothesis	Statement	Study	Outcome
S1-H3	rtBRMS increases phase-specific throughput	Study 1	**Supported**
S1-H4	Gate type moderates the rtBRMS effect on GOT	Study 1	**Supported**
S1-H5	The rtBRMS effect is robust across load quartiles and temporal bands	Study 1	**Supported**
S1-H6a	rtBRMS increases attainment of the FastBoard threshold	Study 1	**Supported**
S1-H6b	rtBRMS increases attainment of the FastDeboard threshold	Study 1	**Supported**
S2-H1	Flow Stability Perception predicts Perceived System Predictability	Study 2	**Supported**
S2-H2a	Perceived Autonomy predicts Perceived System Predictability	Study 2	**Supported**
S2-H2b	Perceived Autonomy predicts Work Engagement	Study 2	**Supported**
S2-H3a	Perceived System Predictability predicts Perceived Performance Contribution	Study 2	**Supported**
S2-H3b	Perceived System Predictability predicts Work Engagement	Study 2	**Supported**
S2-H3c	Perceived System Predictability predicts System Satisfaction	Study 2	**Supported**
S2-H4a	Job Stress Reduction predicts Perceived Performance Contribution	Study 2	**Supported**
S2-H4b	Job Stress Reduction predicts Work Engagement	Study 2	**Supported**

Table 7-1 Outcome of each Hypothesis

Hypothesis	Statement	Study	Outcome
S2-H5a	Comparative Superiority predicts Perceived Performance Contribution	Study 2	**Supported**
S2-H5b	Comparative Superiority predicts Individual Work Performance	Study 2	**Supported**
S2-H6	Perceived Performance Contribution predicts Work Engagement	Study 2	**Supported**
S2-H7a	Work Engagement predicts Individual Work Performance	Study 2	**Supported**
S2-H7b	Perceived Performance Contribution predicts Individual Work Performance	Study 2	**Supported**
S2-H8a	Perceived Performance Contribution predicts Employee Productivity	Study 2	**Supported**
S2-H8b	Individual Work Performance predicts Employee Productivity	Study 2	**Supported**
S2-H9a	Work Engagement predicts System Satisfaction	Study 2	**Supported**
S2-H9b	Employee Productivity predicts System Satisfaction	Study 2	**Supported**
S2-H10	Passenger type moderates FSP → PSP	Study 2 (mod.)	**Not supported**
S2-H11	Interaction frequency moderates PPC → EMP	Study 2 (mod.)	**Not supported**
S2-H12	Level of responsibility moderates PPC → EMP	Study 2 (mod.)	**Not supported**
S2-H13	Years of experience moderates IWP → EMP	Study 2 (mod.)	**Not supported**
S2-H14	Operational area moderates EMP → SS	Study 2 (mod.)	**Supported**

Table 7-1 Outcome of each Hypothesis

Hypothesis	Statement	Study	Outcome
S2-H15	Role moderates PPC → EMP	Study 2 (mod.)	**Supported**
S2-H16	Experience moderates PPC → EMP	Study 2 (mod.)	**Not supported**
S2-H17	Flights per shift moderates IWP → EMP	Study 2 (mod.)	**Not supported**

7.3 THEORETICAL CONTRIBUTIONS

The thesis makes five theoretical contributions, each of which has been argued in detail in Chapter 6 and is summarised here in narrative form. These contributions advance the academic understanding of how rule-based flow control reshapes both operational performance and operator cognition, and they do so by occupying a position that bridges two literatures - airport operations research and human-automation interaction - that have rarely been brought into the same conversation.

The first theoretical contribution is a reframing of turnaround management itself. The dominant tradition in airport operations has treated boarding as a sequencing problem: which passengers should board in which order, and how can the order be optimised under various assumptions about passenger compliance, baggage stowage, and aisle interference? The simulation literature on this question is extensive (Steffen and Hotchkiss, 2012; Schultz, 2018; Jaehn and Neumann, 2015; Moreira et al., 2023) and has produced incremental improvements that depend on idealised conditions seldom replicated in live operations. The present work advances a different conceptual claim. Variance suppression at the door-tunnel-aisle interface, not seat-order optimisation, is the operative lever for window contraction and milestone reliability. Once arrival variability is suppressed, the same cabin geometry that resists rearrangement under sequencing optimisation accommodates passengers smoothly under paced flow. This is not a refinement of the sequencing tradition; it is a different framing of what kind of problem turnaround performance actually is. The implication for the field is that boarding optimisation has been operating on a secondary lever while leaving the primary lever - inflow variance -

untouched. The field-causal evidence presented in this thesis demonstrates, for the first time, that the primary lever is both available and effective under live heterogeneity. Three portable design principles underpin the reframing: pacing must precede policy, because uncontrolled arrival streams overwhelm any local sequencing rule; routing must be topology-aware, because shared physical thresholds otherwise generate cross-stream interference even under disciplined sequences; and milestones must be governed as constraints rather than monitored as exogenous targets, because their reliability is an output of stabilised flow rather than an input that managerial escalation can manufacture. These principles travel beyond aviation to any service system with shared physical infrastructure operating near saturation.

The second theoretical contribution provides field-causal evidence for a prediction that has been theoretically articulated but empirically untested at the gate level: namely, that the heavy-traffic regime of Kingman's approximation operates with the magnitudes the theory predicts. In a G/G/1 queue near saturation, expected waiting time scales with the sum of squared coefficients of variation of arrival and service processes, divided by twice the complement of utilisation. At the utilisations characteristic of peak boarding banks, even modest reductions in arrival-side variance are predicted to yield disproportionately large contractions in waiting and in phase duration. The boarding-window compression and the gate-occupation-time reduction observed in Study 1 are consistent with this prediction, and the gate-complexity moderation provides the empirical confirmation that benefits scale with architectural complexity in the way that Pellegrini, Castelli and Pesenti (2017) modelled and Rott, Schultz and Fricke (2023) anticipated through process mining but did not directly test through intervention. The contribution is therefore not a new theoretical claim but a calibration of an existing one in a setting where calibration has not previously been possible. The variance-propagation logic formalised in factory physics (Hopp and Spearman, 2011) is shown to hold across the full turnaround sequence rather than within boarding alone, providing the field-causal counterpart to Evler et al.'s (2022) network-level demonstration of compounding.

The third theoretical contribution concerns the cognitive fulcrum of operator response to flow-control automation. The human-automation interaction tradition has long identified system predictability as one of three pillars of operator reliance on automation, alongside dependability and faith (Lee and See, 2004); subsequent work has documented that predictability-formation paths typically produce medium effects and are sensitive to operator characteristics, expertise, and task demands (Wickens et al., 2015; Endsley, 2017). The present evidence extends this literature in two related ways. First, it demonstrates that physically observable system behaviour - the rhythm of passenger movement at the gate, continuously and redundantly available to all operators - produces a substantially stronger predictability-formation pathway than the indirect-signal contexts that dominate the prior literature. Second, it bounds the context-specificity hypothesis: where system behaviour is opaque, role and expertise moderate operator response (Parasuraman and Riley, 1997); where system behaviour is physically observable, that moderation collapses. The largely null moderation pattern in Study 2 is not a failure of the model to detect context-sensitivity but a specification of where context-sensitivity does and does not apply. This is a refinement of an established theoretical position rather than a contradiction of it, and it suggests a productive future research agenda comparing operator user-experience mechanisms across automation systems with varying degrees of behavioural opacity.

The fourth theoretical contribution is the empirical triangulation of three established frameworks - Job Demands-Resources (Bakker and Demerouti, 2007, 2017), Technology Acceptance Model 2 (Venkatesh and Davis, 2000), and the IS Success Model (DeLone and McLean, 2003) - in a single structural model of operator user-experience response to operational automation. Each framework has produced an extensive literature in its respective domain, but the three have rarely been brought together in a way that allows their respective predictions to be examined concurrently in the same data. The present evidence shows that resource-based engagement (the JD-R prediction), usefulness-based productivity (the TAM2 prediction), and dual-channel satisfaction (the IS Success prediction) all operate concurrently rather than as competing accounts. The magnitudes observed - at the upper bound of each framework's meta-analytic range - suggest that operationally extreme settings provide unusually strong tests of each framework's central

claims, and that the frameworks' predictions hold up well to such tests when the conditions for vivid contextual contrast are met. The triangulation is itself the substantive contribution: not the validation of any one framework against the others, but the empirical demonstration that the three frameworks describe complementary rather than competing mechanisms when applied to a single socio-technical system, with the conditions under which each framework's predictions return at upper-bound magnitudes now specified rather than left implicit.

The fifth theoretical contribution is methodological in its register but substantive in its consequence. The thesis introduces a replicable two-lens evaluation method that links field-experimental operational evidence with PLS-SEM operator user-experience evidence in the same operational setting, supplying both halves of a socio-technical evaluation that neither lens could supply alone. The operational lens, on its own, would have demonstrated that the controller produces measurable gains but would have left unanswered why those gains are sustained over time and whether operators recognise the system's contribution to them. The operator user-experience lens, on its own, would have demonstrated that operators report internally coherent perceptions of stability, predictability, and engagement but would have left unverified whether those perceptions correspond to real changes in the underlying physical process. The integration of the two lenses in the same operational setting is the methodological commitment that allows each lens to compensate for the limitations of the other, and the protocol developed in this thesis is transferable to other socio-technical evaluations in aviation and beyond - to any setting in which an operational technology is intended to produce both physical and user-experience change in the work of frontline operators. This methodological contribution is registered here as a separate contribution rather than as a sub-clause of the substantive contributions because the protocol is itself a portable scholarly product, independent of the specific findings it has generated in the present thesis.

7.4 PRACTICAL CONTRIBUTIONS

The practical contributions of the thesis translate the empirical evidence into specifications precise enough to guide procurement, interface design, training, and

deployment sequencing in airport operations. They are not generic recommendations to "adopt digital tools"; they are grounded in specific path coefficients, effect sizes, and indirect-effect chains documented in Chapter 5 and interpreted in Chapter 6, and they should therefore be read in conjunction with the full set of practice recommendations in Chapter 7 Part 2.

The most consequential practical contribution is an empirically specified deployment priority. The largest absolute benefits accrue at shared-access gate configurations during peak temporal bands - precisely the regimes in which uncontrolled variability is most damaging and in which manual coordination is most fragile. The variance-reduction logic of Kingman's approximation predicts disproportionately larger returns at high-utilisation bottlenecks, and the gate-complexity interaction in Study 1 confirms the prediction empirically. Capital allocation for rtBRMS deployment should therefore follow this priority rather than being distributed uniformly across gate types or rolled out in the easiest configurations first. Pilot programmes should target peak-period stress bands at shared-access gates, where the mechanism's primary advantage can be most clearly demonstrated and where operational learning will accumulate fastest. Deploying in low-variance configurations first would waste the system's primary advantage and risks producing pilot results that understate the system's true capability.

The second practical contribution concerns human-machine interface design. The structural model places perceived system predictability at the centre of the operator user-experience mechanism: it is the strongest single relationship in the model, it transmits flow-stability perceptions to contribution beliefs, engagement, performance, and satisfaction through twelve significant indirect paths, and without it the operational improvements remain experientially inaccessible to the operators whose engagement and execution sustain them. The practical implication is direct. Real-time stability indicators - signals showing that passenger flow variance is within normal bounds - and next-action previews communicating what the system will do and when should take precedence over retrospective performance summaries in the HMI, because they target the dominant pathway in the operator user-experience mechanism. HMI procurement specifications

should explicitly require predictability-surfacing features, and vendor evaluations should assess interface legibility from the operator's perspective rather than functional capability alone.

The third practical contribution addresses training and the architecture of decision rights. The Role moderation in Study 2 indicates that operators in higher-leverage positions convert contribution beliefs into productivity more efficiently than operators in lower-leverage positions. Training programmes should therefore be differentiated by role rather than designed as a single uniform curriculum. High-leverage operators (gate coordinators, operations controllers) need training that converts contribution beliefs into coordination decisions; lower-leverage operators (security, ground handling) need training in aligning their actions with the system's pacing logic. The autonomy findings - both autonomy-to-predictability and autonomy-to-engagement paths reach significance with substantial coefficients - indicate that system designs should preserve meaningful operator discretion rather than fully automating coordination decisions. Over-automation that eliminates operator choice would simultaneously suppress the predictability-formation channel (because operators who cannot act cannot learn the system's contingencies) and the engagement channel (because autonomy is a primary motivational resource). The recommendation is to design rtBRMS as a decision-support system that recommends actions and surfaces flow information while leaving the final execution decision to the operator - a design philosophy consistent with the human-centred automation principles advocated in the human-factors literature (Lee and See, 2004; Endsley, 2018).

The fourth practical contribution is a change-management framing grounded in the empirical evidence rather than in generic adoption advice. The strength of the stress-reduction-to-engagement pathway - the largest single resource-to-engagement effect in the model - suggests that the most effective way to build operator buy-in during deployment is not through persuasion or training alone, but through demonstrable strain reduction. When operators experience fewer congestion events, fewer firefighting cycles, and less time pressure as a direct result of the system's flow-stabilisation function, their engagement rises naturally through the JD-R motivational process. Communication during deployment

should therefore foreground strain-reduction outcomes ("this system will make your peak periods calmer") rather than efficiency outcomes ("this system will make you faster"), because the former activates the motivational pathway that sustains long-term adoption while the latter risks triggering resistance if operators perceive the system as a productivity-monitoring tool rather than a support mechanism.

The fifth practical contribution is diagnostic. The mediation evidence provides a structured framework for troubleshooting adoption failures. If operators report low satisfaction despite objectively improved flow metrics, the structural chain identifies three possible failure points: the stability improvement is not experientially legible (a flow-stability-to-predictability failure, addressed by HMI redesign); operators cannot attribute the improvement to the system (a predictability-to-contribution failure, addressed by feedback mechanisms); or operators lack the autonomy or role leverage to convert their beliefs into action (a contribution-to-productivity failure, addressed by the decision-rights architecture). The order matters because each upstream failure suppresses everything downstream. This diagnostic logic, derived directly from the structural model, gives operations managers a structured approach to identifying and resolving adoption barriers rather than relying on generic change-management prescriptions, and it establishes a template that can be carried into future evaluations of other operational automation systems. The same diagnostic logic, interface legibility first, attribution feedback second, decision-rights architecture third, has parallels in adjacent operational-automation domains where execution-layer technologies must be made experientially accessible to the operators who run them (Moheb et al., 2026), and the protocol developed here is intended to travel into those settings as much as into the wider aviation context.

7.5 RECOMMENDATIONS FOR PRACTICE

The recommendations that follow distil the empirical evidence into actions for operations managers, HMI designers, training leads, and procurement teams. They are written as continuous reasoning rather than as a checklist, because the decisions to which they speak are interdependent: deployment priority, interface design, training, decision rights, and change-management framing are not separable choices but parts of a single coherent implementation

philosophy. The reasoning has been argued in detail in the discussion chapter and the contributions section above; what follows is the implementation-facing distillation.

An rtBRMS deployment should begin where variance is born. (R1 - Deploy where variance is born.) The variance-reduction logic of Kingman's heavy-traffic approximation, confirmed empirically by the gate-complexity moderation in Study 1, indicates that the largest absolute returns accrue at shared-access gate configurations operating under peak-period stress conditions. Capital allocation should follow this priority rather than uniform rollout: pilot programmes at low-variance gates would waste the system's primary advantage and risk producing pilot results that understate the system's true capability. Beginning with shared-access complexes during peak banks does the opposite. It maximises the empirical contrast between the regulated and unregulated regimes, builds organisational confidence on the basis of unambiguous gains, and produces operational learning at the highest possible rate.

The human-machine interface must surface stability and the next action, not retrospective performance. (R2 - Design interfaces that surface stability and the near future.) The structural model places perceived system predictability at the centre of the operator user-experience mechanism, and predictability arises from continuously observable evidence about the system's behaviour rather than from after-the-fact summaries of how the system performed. Interface specifications should therefore prioritise real-time stability indicators communicating that flow variance is within normal bounds; next-action previews communicating what the system is about to do and when; and trend displays that make the system's decision logic transparent to the operator. Procurement teams evaluating HMI proposals should weight interface legibility and predictability-surfacing features alongside functional capability, because functional capability that is not legible to the operator does not produce the operator user-experience response that sustains adoption over time.

Training should be differentiated by operational leverage rather than designed as a uniform curriculum. (R3 - Differentiate training by operational leverage.) The Role

moderation in Study 2 indicates that operators in higher-leverage positions convert contribution beliefs into productivity more efficiently than operators in lower-leverage positions, and the autonomy paths indicate that engagement and predictability formation depend on the operator's capacity to act on the system's outputs. High-leverage roles - gate coordinators, operations controllers - need training that converts contribution beliefs into coordination decisions, with explicit guidance on how to read the system's pacing and routing recommendations and how to integrate them with their own situational judgement. Lower-leverage roles - security, ground handling - need training in aligning their actions with the system's flow logic so that the operator's micro-decisions reinforce rather than disrupt the regulated cadence. A single uniform curriculum under-serves both groups; differentiated training matches each role's operational position to the cognitive demands of the regulated regime.

The architecture of decision rights should preserve operator discretion. (R4 - Preserve operator discretion in the decision-rights architecture.) Both the autonomy-to-predictability path and the autonomy-to-engagement path reach significance with substantial coefficients, indicating that the cognitive and motivational mechanisms through which operators internalise rtBRMS depend on their continued capacity to make meaningful decisions. Over-automation that eliminates operator choice would simultaneously suppress the predictability-formation channel - because operators who cannot act cannot learn the system's contingencies - and the engagement channel - because autonomy is a primary motivational resource. The recommendation is to design rtBRMS as a decision-support system that recommends actions and surfaces flow information while leaving the final execution decision to the operator. This is consistent with the human-centred automation principles articulated in the human-factors literature (Lee and See, 2004; Endsley, 2018), and it preserves the conditions under which the operator user-experience mechanism documented in Study 2 continues to operate.

Communication during deployment should foreground strain reduction rather than efficiency gains. (R5 - Foreground strain reduction in change-management communication.) The stress-reduction-to-engagement path is the largest single resource-

to-engagement effect in the model, and the JD-R framework predicts that strain-reducing resources sustain engagement over the long term. When operators experience fewer congestion events, fewer firefighting cycles, and less time pressure as a direct consequence of rtBRMS, their engagement rises naturally through the motivational pathway. Communication that frames rtBRMS as "a system that will make your peak periods calmer" therefore activates the pathway that sustains long-term adoption. By contrast, communication that frames the system primarily as "a tool that will make you faster" risks triggering resistance, particularly if operators perceive the system as a productivity-monitoring instrument rather than a support mechanism. The strain-reduction frame is not merely a softer message; it aligns the change-management narrative with the empirical mechanism through which the system actually produces its effects.

Stand-level regularity should be connected to A-CDM milestones. (R6 - Connect stand-level regularity to A-CDM milestones.) The A-CDM tradition has framed milestone reliability as an information-sharing problem to be solved by disciplined exchange between partners. The present evidence reframes it as a flow-control problem: no estimate can be accurate if the underlying process is stochastic and uncontrolled. The two framings are complementary, but the dependence runs in one direction. Stable estimates require stable underlying processes, and rtBRMS produces the stability on which milestone accuracy depends. Operations managers should treat A-CDM milestones as outputs of stabilised flow rather than as exogenous targets, and should feed rtBRMS-generated regularity directly into milestone estimates so that the network consumes a more accurate signal. This change in causal framing - from milestone accuracy as the primary goal to flow stability as the antecedent - has implications for how performance is monitored, how anomalies are diagnosed, and how A-CDM compliance is managed at the institutional level.

Finally, the structural pathway itself should be used as a diagnostic tool when adoption issues arise. (R7 - Use the structural pathway as a diagnostic tool for adoption issues.) If satisfaction lags despite objectively improved flow metrics, the structural chain identifies three possible failure points and the order in which they should be checked. The first check is interface legibility: is the operator perceiving the stability that the system is

producing? If not, the flow-stability-to-predictability transmission is failing, and the fix is HMI redesign that surfaces stability more clearly. The second check is attribution feedback: if the operator perceives stability but does not connect it to the system, the predictability-to-contribution transmission is failing, and the fix is feedback mechanisms that make the system's contribution attributable. The third check is decision-rights architecture: if the operator perceives stability and attributes contribution but cannot act on those beliefs, the contribution-to-productivity transmission is failing, and the fix is the decision-rights architecture rather than the system itself. The order matters because each upstream failure suppresses everything downstream; troubleshooting a downstream failure without first resolving the upstream cause is counter-productive. This diagnostic logic, derived directly from the structural model, gives operations managers a structured approach to identifying and resolving adoption barriers and a way of distinguishing technology problems from organisational problems in the implementation of rtBRMS.

Future Research Directions

The five limitations articulated in Chapter 6 map directly to a structured future-research agenda. First, multi-airport replication is the natural extension of the single-site evidence base. The mechanisms invoked in the present discussion - Kingman's heavy-traffic regime, the variance-propagation logic of factory physics, and the cognitive fulcrum on experientially accessible system behaviour - are theoretically general, but their empirical generalisation across airports of differing scale, traffic mix, and operational culture is a matter for replication rather than extrapolation. A phased multi-airport rollout, designed with comparable measurement protocols across sites, would allow the magnitude of the operational effect to be estimated as a function of site characteristics and would test whether the cognitive fulcrum holds with the same strength under different operator populations.

Second, longitudinal replication of the operator user-experience model would convert the cross-sectional evidence into a temporal account of how the cascade from stability perception to satisfaction unfolds over time. A panel design observing operators repeatedly through the early, middle, and steady-state phases of rtBRMS adoption would

directly test the temporal ordering that the present cross-sectional model presupposes, and would identify whether the magnitudes observed in the present sample reflect the steady state or the early-adoption phase.

Third, comparative studies across automation systems with varying degrees of behavioural opacity would test the bounding hypothesis articulated in Chapter 6. The prediction is specific: as opacity increases, the role-specific moderation pattern of Parasuraman and Riley (1997) should re-emerge, and the magnitude of the cognitive fulcrum should attenuate. A research design that pairs observable systems with partially opaque and fully opaque comparators in matched operational settings would supply the comparative evidence needed to specify the boundary condition rigorously.

Fourth, the network-level extension of the stand-level evidence is a research direction in its own right. The propagation literature (Pyrgiotis et al., 2013; Evler et al., 2022) has theorised that stand-level interventions produce network-level savings exceeding the sum of phase-specific improvements; the present evidence base has not measured the network-level outcome directly. A whole-turnaround integration that links rtBRMS-generated regularity at the stand to A-CDM milestone accuracy at the network interface, and traces the propagation through delay metrics at downstream airports, would supply the network-level test that the stand-level evidence cannot.

Fifth, experimental HMI variation studies would test the operator user-experience mechanism against deliberate manipulations of the predictability-surfacing features that the present evidence identifies as central. The structural model predicts that interfaces with strong stability indicators and next-action previews should produce higher predictability and engagement than interfaces with retrospective summaries alone. A factorial experiment varying interface design, holding the underlying controller constant, would supply the causal evidence on the HMI-design choices that the present observational evidence has only been able to motivate.

These five directions are the natural continuation of the work documented in this thesis, and each is calibrated to a specific limitation of the present evidence base rather

than to a generic call for further work. The agenda is, in this respect, closely tied to what the present thesis has and has not been positioned to test.

7.6 PERSONAL REFLECTION ON THE RESEARCH PROCESS

Two impressions remain after completion of this programme. The first is how quiet a stabilised turn feels. The ramp is not frenetic; it is calm. The absence of drama is not a lack of performance but its signature. In an industry that has long equated visible effort with operational excellence, the discovery that the best-performing turns are the least eventful ones was both counterintuitive and, on reflection, entirely consistent with what queueing theory predicts. A well-governed system does not produce heroic recoveries because it does not produce the crises that require them. Watching that quiet replace what I had previously taken for normal noise reshaped my understanding of what good operations look like in a way that no spreadsheet or path coefficient could have done on its own.

The second impression is how quickly people lean into predictability when it is real. The survey responses did not read like forced enthusiasm; they read like relief. "I can see what the system will do, and now I can do my job." In an industry that has often equated speed with strain, it was striking that governed flow, not exhortation, delivered speed as a by-product. Operators in this study consistently described predictability as a working condition that allowed them to do their job well, rather than as a luxury or as something extracted from them. That observation has changed how I think about technology adoption more broadly. The question I now ask first is not "how do we persuade users to accept the system?" but "have we made the system's behaviour legible enough that acceptance becomes the natural response?" The two questions point in different directions, and the second has, in my experience, produced better answers.

Methodologically, the most useful lesson concerned the value of evidential triangulation. Either study alone would have been suggestive; together they were definitive. The operational study without the operator user-experience study would have left me unable to explain why the gains were sustained and why operators did not resist them; the

operator user-experience study without the operational study would have left me unable to verify that the perceptions corresponded to a real change in the underlying process rather than to a generalised disposition toward favourable answers. Each lens compensated for the limitations of the other, and the discipline of running both, sequentially and to publishable standards, will shape every applied evaluation I undertake in future. The two-lens protocol is not merely a methodological convenience; it is a structural commitment to the proposition that complex socio-technical systems cannot be evaluated from a single vantage point.

Personally, the work changed how I think about the relationship between technology and the people who use it. I began the programme with an engineer's instinct that a sufficiently good system would prove itself. I ended it with a more careful view: technology that improves the world physically still has to be made legible to the people working inside it, or the improvement will not stick. The strongest single coefficient in the operator user-experience model was not about how the system performed but about whether the system's behaviour was experientially accessible. That observation will inform how I scope, evaluate, and communicate technical work for the rest of my professional life. The lesson generalises: the question is not whether a system works but whether the people working alongside it can see that it works, in time to act on what they see.

Finally, the work taught me how to live with limitations honestly. Single-site, quasi-experimental, cross-sectional - each constraint is real, and each will shape what comes next in the research agenda I now intend to pursue. The evidence is strong enough to act on, and the limitations are clear enough to bound the action. Holding both at once, without overstating the certainty of either, is the discipline that the research process has trained, and the discipline that I now take with me into practice. I have come away from this thesis with a sharper appreciation for what it means to make a contribution: not the production of a final answer but the establishment of a position from which the next questions become tractable. The programme of research I now intend to lead - phased multi-airport rollouts, longitudinal panels of operators, experimental HMI variations, and whole-turnaround

integrations - is the natural continuation of the work documented in these chapters, and it will be guided by the same two-lens commitment that shaped this thesis from its outset.

7.7 CLOSING STATEMENT

The thesis began with a question about whether algorithmic flow control could improve turnaround performance and whether frontline staff would recognise and act on that improvement. The answer, supported by 171 flights stratified across a fully crossed forty-eight-cell design, 224 survey respondents, and two complementary analytical frameworks, is yes - and the mechanism through which it works has now been specified with sufficient precision to guide deployment, interface design, training, and future research. The contribution is not a technology recommendation; it is a mechanism-level understanding of how governed flow produces predictable, productive work at the gate.

On the ramp, a rule-based controller reduces effective variability and holds the aisle away from heavy-traffic behaviour: windows are shorter and tighter, rates rise, stand time falls, particularly where topology and load once made manual control brittle. In human terms, operators recognise that cadence as predictability, feel helped rather than hindered by the system, invest more energy in the right places, do better work, and produce more throughput, in patterns that predict beyond the estimation sample. The convergence of objective traces and subjective reports strengthens internal validity; the coherence of boundary conditions across studies strengthens external plausibility. In effect, the two vantage points describe the same arc: stabilise the flow physically, render that stability visible and foreseeable, and the people who run the gate will convert it into dependable, productive work.

The implications are direct. Deploy where variance is born; design interfaces that render stability and the near future legible; teach operators to govern a paced process; connect stand-level regularity to A-CDM milestones so the network can consume it; and attribute contribution explicitly so that usefulness remains a lived, daily reality. The result is not only faster turns. It is a way of working in which predictability is the lever and productivity is the dividend.

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APPENDIXES

APPENDIX A: ETHICS APPROVAL DOCUMENTATION

UNIVERSITY of WORCESTER

EDUCATION, CULTURE AND SOCIETY RESEARCH ETHICS PANEL (ECS REP)
CONFIRMATION OF APPROVAL

1 October 2025

REP CODE: ECS25260003

EMPIRICAL ASSESSMENT OF OPERATIONAL EFFICIENCY GAINS THROUGH RULE-BASED ACCESS MANAGEMENT SYSTEM (RBAMS) IN INTERNATIONAL AIRPORTS

Dear Luca

Thank you for your application for proportionate review ethical approval to the Education, Culture and Society Research Ethics Panel submitted on 7 September 2025.

Your application has been reviewed in accordance with the University of Worcester Ethics Policy and in compliance with the Standard Operating Procedures for proportionate ethical review.

The outcome of the review is that the Panel is now happy to grant this project ethical approval to proceed.

Your research must be undertaken as set out in the approved application for the approval to be valid. You must review your answers to the checklist on an ongoing basis and resubmit for approval where you intend to deviate from the approved research. Any major deviation from the approved application will require a new application for approval.

As part of the University Ethics Policy, the University undertakes an audit of a random sample of approved research. You may be required to complete a questionnaire about your research.

Yours sincerely

Carla Solvason

DR CARLA SOLVASON
Chair – Education, Culture and Society Proportionate Review Panel
Deputy Chair – Education, Culture and Society Research Ethics Panel
ethics@worc.ac.uk

APPENDIX B: SURVEY INSTRUMENT

https://app.onlinesurveys.jisc.ac.uk/s/ucw/boarding-route-management-system-brms-study-2-perception-survey/print?s=cmfayrm1o006ljo02p85jmil9

Real-time Boarding Route ManagementSystem (rtBRMS) Study 2: Perception Survey

Invitation

We would like to invite you to take part in a research project which involves completing ananonymous online survey. Before you decide whether to take part, it is important that you understandwhy the research is being done, what it will involve for you, what information I will ask from you, andwhat I will do with that information. Please take time to read the following information carefully. Thankyou for reading.

What is the purpose of the research?

This study aims to evaluate the perceptions of the Real-time Boarding Route Management System(rtBRMS), a digital gate management system that automates door operations and integrates self-service boarding. While process data (Study 1) demonstrates efficiency gains, this survey (Study 2)explores how security personnel and gate managers perceive rtBRMS in terms of ease of use,usefulness, predictability, organizational readiness, and its effect on workload. The findings will contribute tounderstanding both operational and human dimensions of technology adoption.

Who is undertaking the research?

Principal Investigator: Luca Moheb, Doctoral Researcher (DBA Candidate), University of Worcester

DoS: Dr Sajad Rezaei, Associate Professor and Lead researcher, University of Worcester

Supervisor: Dr Joy Garfield, Associate Professor and Lead researcher, University of Worcester

Who is funding the research?

This study is self-funded as part of a doctoral research project.

Why have I been invited to take part?

You have been invited because you are a security officer, gate manager, or ground staff memberdirectly involved in gate operations. This group was selected because of its hands-on experiencewith rtBRMS and traditional gate systems. We hope to recruit approximately 150–200 participants forthis study.

What will happen if I agree to take part?

If you agree, you will be asked to complete an anonymous online survey.

- The survey will be accessed via a secure link provided by the researcher or through yourorganization's internal communication channels.

- The survey will ask for your perceptions of rtBRMS, including its ease of use, usefulness, predictability, impact on workload, and organizational readiness.

- No personal data will be collected, and all questions are optional.

- The survey will take approximately 10 minutes to complete.

Do I have to take part?

No. Participation is entirely voluntary. If you decide not to take part, it will not affect your employment,training, or relationship with your organization in any way.

At the start of the survey, you will be asked to confirm that:

- You are over 18 years old

- You have read and understood the information provided

- You voluntarily agree to take part in the survey

By submitting the survey, you are providing consent for your responses to be used in the study.

You can withdraw from the study by closing your browser before submission. Once responses aresubmitted, withdrawal is not possible because the survey is anonymous and cannot be traced back toyou.

What are the benefits for me in taking part?

Although there are no direct personal benefits, your participation will help researchers and airportsbetter understand how BRMS is perceived by frontline staff. Findings may support futureimprovements in gate operations, staff training, and system design.

Are there any risks for me if I take part?

The survey has no risk. Some questions may cause you to reflect critically on work processes, but allquestions are optional. If you feel uncomfortable at any point, you may skip a question or exit thesurvey without submitting your responses.

What will you do with my data?

- Your responses will remain completely anonymous.

- No personal or identifying information will be collected.

- Data will be stored securely on dormakaba password-protected systems.

- Results will be summarized in the doctoral thesis, presented at conferences, and may be publishedin academic journals. Only anonymized aggregated data will be shared.

How long will you keep my data for?

All anonymized data will be stored securely for a minimum of 5 years in line with the University ofWorcester's Policy for the Effective Management of Research Data. After this period, the data will besecurely destroyed.

Thank you for taking the time to read this information

If you have any questions or would like further information, please contact:

Researcher: Luca Moheb – mohl1_23@uni.worc.ac.uk

DoS: Dr. Sajad Rezaei – s.rezaei@worc.ac.uk

Supervisor: Dr. Joy Garfield – j.garfield@worc.ac.uk

The University is registered with the Information Commissioner's Office. For more on the Universityapproach to Information Assurance and Security visit: https://informationassurance.wp.worc.ac.uk/.

Allegations of Research Misconduct

To view University of Worcester's Procedures for Dealing with Allegations of Research Misconductplease click here. For information about who to contact please click here.

If you would like to speak to an independent person who is not a member of the research team,please contact the University of Worcester, using the following details:

Michelle Jellis

Secretary to Health & Sciences and Education, Culture & Society Research Ethics Panels

University of Worcester

Henwick Grove

Worcester

WR2 6AJ

ethics@worc.ac.uk1.ELECTRONIC CONSENT: If you have viewed and understand the Participant InformationSheet please select your choice below. By clicking on the "agree" button below youindicate that you: - have read the above information;- voluntarily agree to participate;- are at least 18 years of age.If you do not wish to participate in the research study, pleasedecline participation by clicking on the "disagree" button.*

DisagreeAgree2.

Comparative Evaluation of rtBRMS

Q1. Compared to the traditional system, rtBRMS makes gate and door transitions easier to manage.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q2. rtBRMS reduces the time required to prepare and execute boarding or deboarding.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q3. Coordination between gate staff, security, and ground handlers runs more smoothly when rtBRMS is used.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q4. Overall operational handling performance is improved with rtBRMS compared to the traditional system.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree3.

Operational Experience with rtBRMS - Flow Stability Perception (FSP)

Q5. Passenger movement feels more stable and less erratic when rtBRMS is active.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q6. With rtBRMS, sudden surges or drops in flow are less common.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q7. The boarding and deboarding process feels smoother when rtBRMS is used.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q8. rtBRMS helps maintain a steady pace of passenger movement.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree4.

Operational Experience with rtBRMS - Perceived System Predictability (PSP)

Q9. rtBRMS behaves consistently across comparable gate conditions.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q10. I can anticipate how rtBRMS will act when passenger flows change.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q11. The decisions taken by rtBRMS during boarding or deboarding are predictable.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q12. The routing and pacing actions of rtBRMS are easy to foresee in real time.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree5.

Operational Experience with rtBRMS - Perceived Autonomy (AUT)

Q13. rtBRMS allows me to manage gate timing and sequencing with more control.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q14. I feel able to intervene proactively when unexpected events occur.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q15. Flow stability from rtBRMS gives me greater operational autonomy.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree6.

Operational Experience with rtBRMS - Job Stress Reduction (JSR)

Q16. Peak-time boarding and deboarding feel less stressful with rtBRMS.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q17. I experience less time pressure at the gate when passenger flows are stabilised by rtBRMS.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q18. rtBRMS reduces my concerns about congestion near doors or aisles.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree7.

Operational Experience with rtBRMS - Work Engagement (ENG)

Q19. I feel energised when carrying out my tasks while rtBRMS is in use.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q20. I am enthusiastic about performing gate-related tasks supported by rtBRMS.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q21. I become absorbed in my work during gate operations when rtBRMS is active.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree8.

Operational Experience with rtBRMS - Perceived Performance Contribution (PPC)

Q22. rtBRMS helps me perform my gate tasks more effectively.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q23. rtBRMS contributes to the quality of my work.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q24. rtBRMS supports me in working more efficiently during turnarounds.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree9.

Operational Experience with rtBRMS - Individual Work Performance (IWP)

Q25. I complete my gate tasks accurately and with attention to detail.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q26. I achieve the expected performance level in gate operations.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q27. I handle my workload effectively, even during demanding gate situations.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree10.

Operational Experience with rtBRMS - Employee Productivity (EMP)

Q28. With rtBRMS, I can handle more tasks within the same time frame.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q29. rtBRMS enables higher productivity during gate turnarounds.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Q30. The use of rtBRMS improves overall efficiency in gate operations.

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree11.

Operational Experience with rtBRMS - System Satisfaction (SS)

Q32. Overall, I am satisfied with rtBRMS as a support system for gate operations.

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neutral

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

Q33. rtBRMS meets my expectations as a tool for managing passenger flow.

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neutral

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

Q34. I would prefer to use rtBRMS rather than operate without it.

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neutral

5 = Slightly Agree

6 = Agree

7 = Strongly Agree12.

Role at Airport

Safety PersonnelSecurity PersonnelGate AgentGate ManagerDispatcherGround HandlingSupervisorOther (please specify)13.

Years of Experience in Gate Operations

Less than 1 year1–3 years4–7 years8–15 yearsMore than 15 years14.

Frequency of Interaction with rtBRMS

DailySeveral times per weekOccasionallyRarely15.

Flights Typically Handled per Shift

1–34–67–10More than 1016.

Primary Level of Responsibility for rtBRMS

Direct operation (actively controlling gates)Monitoring and supervisionPassenger assistanceTroubleshooting / technical supportManagement oversight17.

Primary Operational Area

Terminal A (Domestic)Terminal B (International)Remote standsMixed areas18.

Primary Passenger Type

Mainly departuresMainly arrivalsBoth equally

Appendix C.1: GOT_min (S1-H1)

T-test: Group Statistics + Independent Samples Test + Effect Sizes

Group Statistics

	BRMS_Enabled	N	Mean	Std. Deviation	Std. Error Mean
GOT_min	0	74	57,74	3,638	,423
	1	97	44,86	2,291	,233

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
GOT_min	Equal variances assumed	28,310	169	<,001	<,001	12,888	,455	11,989	13,786
	Equal variances not assumed	26,701	115,803	<,001	<,001	12,888	,483	11,932	13,844

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
GOT_min	Cohen's d	2,949	4,370	3,812	4,923
	Hedges' correction	2,963	4,350	3,795	4,901
	Glass's delta	2,291	5,625	4,772	6,472

UNIANOVA: Levene's + Tests of Between-Subjects Effects + Estimated Marginal Means + Pairwise Comparisons

Between-Subjects Factors

		N
BRMS_Enabled	0	74
	1	97

Descriptive Statistics

Dependent Variable: GOT_min

BRMS_Enabled	Mean	Std. Deviation	N
0	57,74	3,638	74
1	44,86	2,291	97
Total	50,43	7,047	171

Levene's Test of Equality of Error Variances[a]

Dependent Variable: GOT_min

F	df1	df2	Sig.
27,853	1	169	<,001

Tests of Between-Subjects Effects

Dependent Variable: GOT_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected Model	7737,526[a]	5	1547,505	362,465	<,001	,917	1812,324	1,000
Intercept	650,925	1	650,925	152,463	<,001	,480	152,463	1,000
Passenger_Count	374,479	1	374,479	87,712	<,001	,347	87,712	1,000
Flights_per_Gate_per_Day	8,740	1	8,740	2,047	,154	,012	2,047	,296
Shared_Access_Points	292,405	1	292,405	68,489	<,001	,293	68,489	1,000
Self_Checkin_Used	51,107	1	51,107	11,970	<,001	,068	11,970	,931
BRMS_Enabled	4842,970	1	4842,970	1134,346	<,001	,873	1134,346	1,000
Error	704,450	165	4,269					
Total	443374,000	171						
Corrected Total	8441,977	170						

a. R Squared = ,917 (Adjusted R Squared = ,914)

b. Computed using alpha = ,05

Estimated Marginal Means

BRMS_Enabled

Estimates

Dependent Variable: GOT_min

BRMS_Enabled	Mean	Std. Error	95% Confidence Interval	
			Lower Bound	Upper Bound
0	57,413[a]	,261	56,898	57,927
1	45,108[a]	,224	44,667	45,549

a. Covariates appearing in the model are evaluated at the following values: Passenger_Count = 142,01, Flights_per_Gate_per_Day = 9,53, Shared_Access_Points = 1,94, Self_Checkin_Used = ,60.

Pairwise Comparisons

Dependent Variable: GOT_min

(I) BRMS_Enabled	(J) BRMS_Enabled	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
0	1	12,305*	,365	<,001	11,583	13,026
1	0	-12,305*	,365	<,001	-13,026	-11,583

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable: GOT_min

	Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
Contrast	4842,970	1	4842,970	1134,346	<,001	,873	1134,346	1,000
Error	704,450	165	4,269					

The F tests the effect of BRMS_Enabled. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = ,05

Appendix C.2: Deboard_Window_min and Board_Window_min (S1-H2)

T-tests for both DVs (Group Statistics + Independent Samples Test + Effect Sizes)

T-Test

Group Statistics

	BRMS_Enabled	N	Mean	Std. Deviation	Std. Error Mean
Deboard_Window_min	0	74	24,1876	1,20286	,13983
	1	97	22,2066	,97708	,09921
Board_Window_min	0	74	25,7114	1,64397	,19111
	1	97	21,6566	1,49300	,15159

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Deboard_Window_min	Equal variances assumed	11,879	169	<,001	<,001	1,98097	,16676	1,65177	2,31017
	Equal variances not assumed	11,554	138,335	<,001	<,001	1,98097	,17145	1,64197	2,31997
Board_Window_min	Equal variances assumed	16,840	169	<,001	<,001	4,05475	,24078	3,57943	4,53008
	Equal variances not assumed	16,623	148,929	<,001	<,001	4,05475	,24393	3,57274	4,53677

Independent Samples Effect Sizes

				95% Confidence Interval	
		Standardizer[a]	Point Estimate	Lower	Upper
Deboard_Window_min	Cohen's d	1,08041	1,834	1,471	2,192
	Hedges' correction	1,08523	1,825	1,465	2,182
	Glass's delta	,97708	2,027	1,608	2,441
Board_Window_min	Cohen's d	1,56001	2,599	2,187	3,007
	Hedges' correction	1,56697	2,588	2,177	2,994
	Glass's delta	1,49300	2,716	2,224	3,201

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

GLM for both DVs (Between-Subjects Effects + EMMEANS)

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Deboard_Window_min * BRMS_Enabled	171	100,0%	0	0,0%	171	100,0%
Board_Window_min * BRMS_Enabled	171	100,0%	0	0,0%	171	100,0%

Report

BRMS_Enabled		Deboard_Window_min	Board_Window_min
0	Mean	24,1876	25,7114
	N	74	74
	Std. Deviation	1,20286	1,64397
1	Mean	22,2066	21,6566
	N	97	97
	Std. Deviation	,97708	1,49300
Total	Mean	23,0639	23,4113
	N	171	171
	Std. Deviation	1,45924	2,54538

```
T-TEST GROUPS=BRMS_Enabled(0 1)
  /MISSING=ANALYSIS
  /VARIABLES=Deboard_Window_min Board_Window_min
  /ES DISPLAY(TRUE)
  /HOMOGENEITY DISPLAY(FALSE)
  /CRITERIA=CI(.95)
```

Tests of Between-Subjects Effects

Dependent Variable: Deboard_Window_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	278,508[a]	3	92,836	185,696	<,001
Intercept	4251,718	1	4251,718	8504,542	<,001
Passenger_Count	42,792	1	42,792	85,596	<,001
Shared_Access_Points	63,116	1	63,116	126,248	<,001
BRMS_Enabled	156,291	1	156,291	312,624	<,001
Error	83,489	167	,500		
Total	91324,015	171			
Corrected Total	361,997	170			

a. R Squared = ,769 (Adjusted R Squared = ,765)

```
UNIANOVA Board_Window_min BY BRMS_Enabled WITH Passenger_Count Shared_Access_Points
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PRINT ETASQ
  /CRITERIA=ALPHA(.05)
  /DESIGN=Passenger_Count Shared_Access_Points BRMS_Enabled.
```

Tests of Between-Subjects Effects

Dependent Variable: Deboard_Window_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	278,508[a]	3	92,836	185,696	<,001
Intercept	4251,718	1	4251,718	8504,542	<,001
Passenger_Count	42,792	1	42,792	85,596	<,001
Shared_Access_Points	63,116	1	63,116	126,248	<,001
BRMS_Enabled	156,291	1	156,291	312,624	<,001
Error	83,489	167	,500		
Total	91324,015	171			
Corrected Total	361,997	170			

a. R Squared = ,769 (Adjusted R Squared = ,765)

```
UNIANOVA Board_Window_min BY BRMS_Enabled WITH Passenger_Count Shared_Access_Points
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /PRINT ETASQ
  /CRITERIA=ALPHA(.05)
  /DESIGN=Passenger_Count Shared_Access_Points BRMS_Enabled.
```

Appendix C.3: Throughput_deboard_pax_min and Throughput_board_pax_min (S1-H3)
T-tests for both DVs

T-Test

Group Statistics

	BRMS_Enabled	N	Mean	Std. Deviation	Std. Error Mean
Throughput_deboard_pax_min	0	74	11,9366	,56577	,06577
	1	97	13,5127	,57262	,05814
Throughput_board_pax_min	0	74	10,9168	1,13477	,13191
	1	97	12,6112	,96826	,09831

Independent Samples Test

		t-test for Equality of Means							
				Significance				95% Confidence Interval of the Difference	
		t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Throughput_deboard_pax_min	Equal variances assumed	-17,925	169	<,001	<,001	-1,57606	,08793	-1,74964	-1,40248
	Equal variances not assumed	-17,954	158,207	<,001	<,001	-1,57606	,08778	-1,74944	-1,40268
Throughput_board_pax_min	Equal variances assumed	-10,521	169	<,001	<,001	-1,69448	,16105	-2,01241	-1,37655
	Equal variances not assumed	-10,300	143,054	<,001	<,001	-1,69448	,16452	-2,01968	-1,36928

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval Lower	Upper
Throughput_deboard_pax_min	Cohen's d	,56967	-2,767	-3,187	-2,342
	Hedges' correction	,57222	-2,754	-3,173	-2,332
	Glass's delta	,57262	-2,752	-3,242	-2,257
Throughput_board_pax_min	Cohen's d	1,04345	-1,624	-1,971	-1,274
	Hedges' correction	1,04811	-1,617	-1,962	-1,268
	Glass's delta	,96826	-1,750	-2,138	-1,357

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control (i.e., the second) group.

Univariate Analysis of Variance

Between-Subjects Factors

		N
BRMS_Enabled	0	74
	1	97

Tests of Between-Subjects Effects

Dependent Variable: Throughput_deboard_pax_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	120,318[a]	4	30,079	128,704	<,001	,756
Intercept	1384,359	1	1384,359	5923,384	<,001	,973
Passenger_Count	,021	1	,021	,088	,767	,001
Shared_Access_Points	15,927	1	15,927	68,147	<,001	,291
Self_Checkin_Used	,123	1	,123	,525	,470	,003
BRMS_Enabled	84,046	1	84,046	359,616	<,001	,684
Error	38,796	166	,234			
Total	28310,058	171				
Corrected Total	159,114	170				

a. R Squared = ,756 (Adjusted R Squared = ,750)

Univariate Analysis of Variance

Between-Subjects Factors

		N
BRMS_Enabled	0	74
	1	97

Tests of Between-Subjects Effects

Dependent Variable: Throughput_board_pax_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	261,607[a]	4	65,402	252,936	<,001	,859
Intercept	1008,819	1	1008,819	3901,513	<,001	,959
Passenger_Count	,079	1	,079	,305	,582	,002
Shared_Access_Points	6,280	1	6,280	24,288	<,001	,128
Self_Checkin_Used	134,905	1	134,905	521,732	<,001	,759
BRMS_Enabled	20,824	1	20,824	80,534	<,001	,327
Error	42,923	166	,259			
Total	24430,197	171				
Corrected Total	304,530	170				

a. R Squared = ,859 (Adjusted R Squared = ,856)

Means

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
Throughput_deboard_pax_min * BRMS_Enabled	171	100,0%	0	0,0%	171	100,0%
Throughput_board_pax_min * BRMS_Enabled	171	100,0%	0	0,0%	171	100,0%

Report

BRMS_Enabled		Throughput_deboard_pax_min	Throughput_board_pax_min
0	Mean	11,9366	10,9168
	N	74	74
	Std. Deviation	,56577	1,13477
1	Mean	13,5127	12,6112
	N	97	97
	Std. Deviation	,57262	,96826
Total	Mean	12,8306	11,8780
	N	171	171
	Std. Deviation	,96745	1,33841

Appendix C.4: GOT_min × Gate_Type interaction (S1-H4)

GLM with interaction term (Between-Subjects Effects showing rtBRMS×Gate_Type F=4.225, p=.007)

Univariate Analysis of Variance

Between-Subjects Factors

		N
BRMS_Enabled	0	74
	1	97
Gate_Type	1	32
	2	53
	3	59
	4	27

Tests of Between-Subjects Effects

Dependent Variable: GOT_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	7995,960[a]	11	726,905	259,134	<,001	,947
Intercept	773,984	1	773,984	275,917	<,001	,634
Passenger_Count	394,951	1	394,951	140,796	<,001	,470
Shared_Access_Points	7,177	1	7,177	2,558	,112	,016
Self_Checkin_Used	24,067	1	24,067	8,580	,004	,051
Flights_per_Gate_per_Day	6,669	1	6,669	2,377	,125	,015
BRMS_Enabled	4447,190	1	4447,190	1585,373	<,001	,909
Gate_Type	230,238	3	76,746	27,359	<,001	,340
BRMS_Enabled * Gate_Type	35,556	3	11,852	4,225	,007	,074
Error	446,017	159	2,805			
Total	443374,000	171				
Corrected Total	8441,977	170				

a. R Squared = ,947 (Adjusted R Squared = ,944)

Between-Subjects Factors

		N
BRMS_Enabled	0	74
	1	97
Gate_Type	1	32
	2	53
	3	59
	4	27

Descriptive Statistics

Dependent Variable: GOT_min

BRMS_Enabled	Gate_Type	Mean	Std. Deviation	N
0	1	54,15	3,555	13
	2	55,82	2,834	17
	3	58,97	2,442	31
	4	60,92	2,871	13
	Total	57,74	3,638	74
1	1	42,89	1,487	19
	2	44,22	1,551	36
	3	45,79	2,079	28
	4	47,29	2,301	14
	Total	44,86	2,291	97
Total	1	47,47	6,143	32
	2	47,94	5,829	53
	3	52,71	7,012	59
	4	53,85	7,394	27
	Total	50,43	7,047	171

Levene's Test of Equality of Error Variances[a]

Dependent Variable: GOT_min

F	df1	df2	Sig.
10,750	7	163	<,001

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Passenger_Count + Shared_Access_Points + Self_Checkin_Used + Flights_per_Gate_per_Day + BRMS_Enabled + Gate_Type + BRMS_Enabled * Gate_Type

Tests of Between-Subjects Effects

Dependent Variable: GOT_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	7995,960[a]	11	726,905	259,134	<,001	,947
Intercept	773,984	1	773,984	275,917	<,001	,634
Passenger_Count	394,951	1	394,951	140,796	<,001	,470
Shared_Access_Points	7,177	1	7,177	2,558	,112	,016
Self_Checkin_Used	24,067	1	24,067	8,580	,004	,051
Flights_per_Gate_per_Day	6,669	1	6,669	2,377	,125	,015
BRMS_Enabled	4447,190	1	4447,190	1585,373	<,001	,909
Gate_Type	230,238	3	76,746	27,359	<,001	,340
BRMS_Enabled * Gate_Type	35,556	3	11,852	4,225	,007	,074
Error	446,017	159	2,805			
Total	443374,000	171				
Corrected Total	8441,977	170				

a. R Squared = ,947 (Adjusted R Squared = ,944)

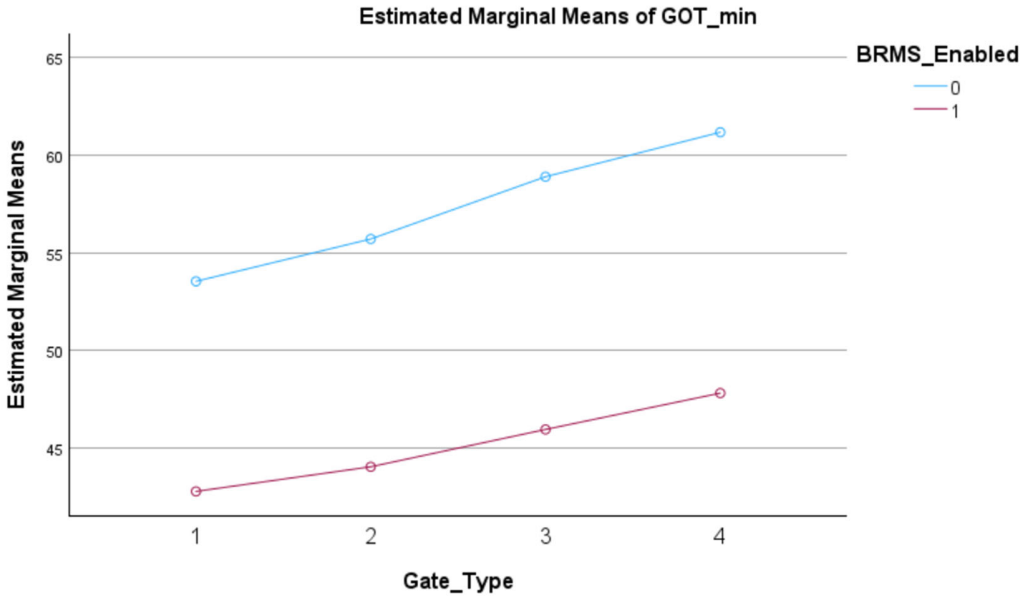
Estimated Marginal Means

BRMS_Enabled * Gate_Type

Dependent Variable: GOT_min

BRMS_Enabled	Gate_Type	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
0	1	53,593[a]	,559	52,489	54,696
	2	55,753[a]	,426	54,911	56,595
	3	58,929[a]	,330	58,277	59,581
	4	61,199[a]	,575	60,063	62,336
1	1	42,814[a]	,503	41,821	43,807
	2	44,072[a]	,317	43,447	44,697
	3	45,978[a]	,334	45,319	46,637
	4	47,835[a]	,544	46,759	48,910

a. Covariates appearing in the model are evaluated at the following values: Passenger_Count = 142,01, Shared_Access_Points = 1,94, Self_Checkin_Used = ,60, Flights_per_Gate_per_Day = 9,53.



Covariates appearing in the model are evaluated at the following values: Passenger_Count = 142,01, Shared_Access_Points = 1,94, Self_Checkin_Used = ,60, Flights_per_Gate_per_Day = 9,53

Appendix C.5: GOT_min × Load/Temporal factors (S1-H5)

RANK

Created Variables[a]

Source Variable	Function	New Variable	Label
Passenger_Count[b]	Rank	RAN003	Rank of Passenger_Count
	Percentile Group[c]	NTI003	Percentile Group of Passenger_Count

a. Mean rank of tied values is used for ties.

b. Ranks are in ascending order.

c. 4 groups are generated.

Frequencies

```
[DataSet1] C:\Users\moheblu\Documents\DEC2025\20251208_MHD_BRMS_Study_170flights_48strata.sav
```

Statistics

Load_Quartile

N	Valid	171
	Missing	0

Load_Quartile

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	43	25,1	25,1	25,1
	2	43	25,1	25,1	50,3
	3	43	25,1	25,1	75,4
	4	42	24,6	24,6	100,0
	Total	171	100,0	100,0	

```
MEANS TABLES=GOT_min BY Load_Quartile BRMS_Enabled
  /CELLS=MEAN COUNT STDDEV.
```

GOT_min * BRMS_Enabled

GOT_min

BRMS_Enabled	Mean	N	Std. Deviation
0	57,74	74	3,638
1	44,86	97	2,291
Total	50,43	171	7,047

```
UNIANOVA GOT_min BY BRMS_Enabled Load_Quartile Time_of_Day Day_Type WITH Passenger_Count
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /EMMEANS=TABLES(BRMS_Enabled*Load_Quartile) WITH(Passenger_Count=MEAN) COMPARE(BRMS_Enabled)
    ADJ(BONFERRONI)
  /EMMEANS=TABLES(BRMS_Enabled*Load_Quartile) WITH(Passenger_Count=MEAN) COMPARE(Load_Quartile)
    ADJ(BONFERRONI)
  /PRINT ETASQ DESCRIPTIVE HOMOGENEITY
  /CRITERIA=ALPHA(.05)
  /DESIGN=Passenger_Count BRMS_Enabled Load_Quartile Time_of_Day Day_Type
    BRMS_Enabled*Load_Quartile BRMS_Enabled*Time_of_Day BRMS_Enabled*Day_Type Load_Quartile*Time_of_Day
    Load_Quartile*Day_Type Time_of_Day*Day_Type BRMS_Enabled*Load_Quartile*Time_of_Day
    BRMS_Enabled*Load_Quartile*Day_Type BRMS_Enabled*Time_of_Day*Day_Type
    Load_Quartile*Time_of_Day*Day_Type BRMS_Enabled*Load_Quartile*Time_of_Day*Day_Type.
```

Univariate Analysis of Variance

Between-Subjects Factors

		Value Label	N
BRMS_Enabled	0		74
	1		97
Load_Quartile	1	1	43
	2	2	43
	3	3	43
	4	4	42
Time_of_Day	1		66
	2		53
	3		52
Day_Type	0		142
	1		29

Descriptive Statistics

Dependent Variable: GOT_min

BRMS_Enabled	Load_Quartile	Time_of_Day	Day_Type	Mean	Std. Deviation	N
0	1	1	0	53,00	3,464	5
			1	57,33	2,082	3
			Total	54,63	3,623	8
		2	0	56,50	,707	2
			1	54,00	2,646	3
			Total	55,00	2,345	5
		3	0	57,75	3,096	4
			1	54,50	4,950	2
			Total	56,67	3,670	6
		Total	0	55,36	3,613	11
			1	55,37	3,068	8
			Total	55,37	3,303	19
	2	1	0	56,75	3,655	8
			1	58,00	.	1
			Total	56,89	3,444	9
		2	0	59,17	1,472	6
			1	54,00	.	1
			Total	58,43	2,370	7
		3	0	52,00	2,646	3
			1	62,00	.	1
			Total	54,50	5,447	4
		Total	0	56,76	3,717	17
			1	58,00	4,000	3

		Total	56,95	3,677	20
3	1	0	58,50	2,563	8
		1	59,00	.	1
		Total	58,56	2,404	9
	2	0	60,50	,707	2
		Total	60,50	,707	2
	3	0	58,25	1,500	4
		1	58,50	,707	2
		Total	58,33	1,211	6
	Total	0	58,71	2,164	14
		1	58,67	,577	3
		Total	58,71	1,961	17
4	1	0	59,63	3,462	8
		1	58,00	.	1
		Total	59,44	3,283	9
	2	0	61,80	3,564	5
		Total	61,80	3,564	5
	3	0	58,67	3,786	3
		1	64,00	.	1
		Total	60,00	4,082	4
	Total	0	60,13	3,519	16
		1	61,00	4,243	2
		Total	60,22	3,474	18
Total	1	0	57,38	3,877	29
		1	57,83	1,472	6
		Total	57,46	3,567	35
	2	0	59,87	2,774	15

			1	54,00	2,160	4
			Total	58,63	3,578	19
		3	0	56,86	3,613	14
			1	58,67	4,457	6
			Total	57,40	3,858	20
		Total	0	57,90	3,698	58
			1	57,19	3,468	16
			Total	57,74	3,638	74
1	1	1	0	43,13	1,553	8
			1	45,00	.	1
			Total	43,33	1,581	9
		2	0	42,64	1,027	11
			1	43,00	.	1
			Total	42,67	,985	12
		3	0	44,33	1,528	3
			Total	44,33	1,528	3
		Total	0	43,05	1,362	22
			1	44,00	1,414	2
			Total	43,12	1,361	24
	2	1	0	43,00	1,581	5
			Total	43,00	1,581	5
		2	0	44,86	1,952	7
			1	45,00	.	1
			Total	44,88	1,808	8
		3	0	43,70	1,567	10
			Total	43,70	1,567	10
		Total	0	43,91	1,770	22

		1	45,00	.	1
		Total	43,96	1,745	23
3	1	0	46,33	2,338	6
		1	43,67	1,155	3
		Total	45,44	2,351	9
	2	0	45,00	1,265	6
		Total	45,00	1,265	6
	3	0	46,22	2,167	9
		1	48,00	,000	2
		Total	46,55	2,067	11
	Total	0	45,90	1,998	21
		1	45,40	2,510	5
		Total	45,81	2,059	26
4	1	0	45,14	2,035	7
		1	47,00	.	1
		Total	45,38	1,996	8
	2	0	47,88	2,416	8
		Total	47,88	2,416	8
	3	0	46,75	1,500	4
		1	45,25	1,708	4
		Total	46,00	1,690	8
	Total	0	46,63	2,362	19
		1	45,60	1,673	5
		Total	46,42	2,244	24
Total	1	0	44,38	2,264	26
		1	44,60	1,673	5
		Total	44,42	2,157	31

		2	0	44,88	2,600	32
			1	44,00	1,414	2
			Total	44,82	2,540	34
		3	0	45,12	2,142	26
			1	46,17	1,941	6
			Total	45,31	2,117	32
		Total	0	44,80	2,353	84
			1	45,23	1,878	13
			Total	44,86	2,291	97
Total	1	1	0	46,92	5,515	13
			1	54,25	6,397	4
			Total	48,65	6,383	17
		2	0	44,77	5,294	13
			1	51,25	5,909	4
			Total	46,29	5,966	17
		3	0	52,00	7,550	7
			1	54,50	4,950	2
			Total	52,56	6,858	9
		Total	0	47,15	6,330	33
			1	53,10	5,527	10
			Total	48,53	6,599	43
	2	1	0	51,46	7,557	13
			1	58,00	.	1
			Total	51,93	7,468	14
		2	0	51,46	7,612	13
			1	49,50	6,364	2
			Total	51,20	7,282	15

	3	0	45,62	4,032	13
		1	62,00	.	1
		Total	46,79	5,846	14
	Total	0	49,51	7,018	39
		1	54,75	7,274	4
		Total	50,00	7,121	43
3	1	0	53,29	6,684	14
		1	47,50	7,724	4
		Total	52,00	7,129	18
	2	0	48,88	7,259	8
		Total	48,88	7,259	8
	3	0	49,92	6,089	13
		1	53,25	6,076	4
		Total	50,71	6,070	17
	Total	0	51,03	6,684	35
		1	50,38	7,130	8
		Total	50,91	6,686	43
4	1	0	52,87	7,981	15
		1	52,50	7,778	2
		Total	52,82	7,716	17
	2	0	53,23	7,574	13
		Total	53,23	7,574	13
	3	0	51,86	6,817	7
		1	49,00	8,515	5
		Total	50,67	7,340	12
	Total	0	52,80	7,411	35
		1	50,00	7,832	7
	Total	0	52,80	7,411	35
		1	50,00	7,832	7
		Total	52,33	7,459	42
Total	1	0	51,24	7,283	55
		1	51,82	7,068	11
		Total	51,33	7,197	66
	2	0	49,66	7,536	47
		1	50,67	5,465	6
		Total	49,77	7,295	53
	3	0	49,23	6,282	40
		1	52,42	7,305	12
		Total	49,96	6,598	52
	Total	0	50,15	7,109	142
		1	51,83	6,677	29
		Total	50,43	7,047	171

Levene's Test of Equality of Error Variances[a]

Dependent Variable: GOT_min

F	df1	df2	Sig.
1,884	40	130	,004

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + Passenger_Count + BRMS_Enabled + Load_Quartile + Time_of_Day + Day_Type + BRMS_Enabled * Load_Quartile + BRMS_Enabled * Time_of_Day + BRMS_Enabled * Day_Type + Load_Quartile * Time_of_Day + Load_Quartile * Day_Type + Time_of_Day * Day_Type + BRMS_Enabled * Load_Quartile * Time_of_Day + BRMS_Enabled * Load_Quartile * Day_Type + BRMS_Enabled * Time_of_Day * Day_Type + Load_Quartile * Time_of_Day * Day_Type + BRMS_Enabled * Load_Quartile * Time_of_Day * Day_Type

Tests of Between-Subjects Effects

Dependent Variable: GOT_min

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	7762,347[a]	41	189,326	35,936	<,001	,919
Intercept	3519,776	1	3519,776	668,087	<,001	,838
Passenger_Count	24,044	1	24,044	4,564	,035	,034
BRMS_Enabled	2507,117	1	2507,117	475,874	<,001	,787
Load_Quartile	1,448	3	,483	,092	,965	,002
Time_of_Day	10,097	2	5,048	,958	,386	,015
Day_Type	1,170	1	1,170	,222	,638	,002
BRMS_Enabled * Load_Quartile	5,493	3	1,831	,348	,791	,008
BRMS_Enabled * Time_of_Day	1,881	2	,941	,179	,837	,003
BRMS_Enabled * Day_Type	,052	1	,052	,010	,921	,000
Load_Quartile * Time_of_Day	16,919	6	2,820	,535	,781	,024
Load_Quartile * Day_Type	11,672	3	3,891	,738	,531	,017
Time_of_Day * Day_Type	34,524	2	17,262	3,276	,041	,048
BRMS_Enabled * Load_Quartile * Time_of_Day	69,579	6	11,597	2,201	,047	,093
BRMS_Enabled * Load_Quartile * Day_Type	3,440	3	1,147	,218	,884	,005
BRMS_Enabled * Time_of_Day * Day_Type	11,983	2	5,992	1,137	,324	,017

Load_Quartile * Time_of_Day	16,919	6	2,820	,535	,781	,024
Load_Quartile * Day_Type	11,672	3	3,891	,738	,531	,017
Time_of_Day * Day_Type	34,524	2	17,262	3,276	,041	,048
BRMS_Enabled * Load_Quartile * Time_of_Day	69,579	6	11,597	2,201	,047	,093
BRMS_Enabled * Load_Quartile * Day_Type	3,440	3	1,147	,218	,884	,005
BRMS_Enabled * Time_of_Day * Day_Type	11,983	2	5,992	1,137	,324	,017

Load_Quartile * Time_of_Day * Day_Type	109,058	4	27,265	5,175	<,001	,138
BRMS_Enabled * Load_Quartile * Time_of_Day * Day_Type	26,803	1	26,803	5,087	,026	,038
Error	679,629	129	5,268			
Total	443374,000	171				
Corrected Total	8441,977	170				

a. R Squared = ,919 (Adjusted R Squared = ,894)

Estimated Marginal Means

1. BRMS_Enabled * Load_Quartile

Estimates

Dependent Variable: GOT_min

BRMS_Enabled	Load_Quartile	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
0	1	57,397[a]	1,042	55,334	59,459
	2	57,225[a]	,737	55,767	58,683
	3	58,489[a,b]	,740	57,026	59,953
	4	58,755[a,b]	1,080	56,618	60,892
1	1	45,531[a,b]	1,157	43,242	47,820
	2	44,338[a,b]	,696	42,962	45,714
	3	45,215[a,b]	,597	44,034	46,396
	4	44,653[a,b]	1,022	42,632	46,675

a. Covariates appearing in the model are evaluated at the following values: Passenger_Count = 142,01.

b. Based on modified population marginal mean.

Pairwise Comparisons

Dependent Variable: GOT_min

Load_Quartile	(I) BRMS_Enabled	(J) BRMS_Enabled	Mean Difference (I-J)	Std. Error	Sig.[d]	95% Confidence Interval for Difference[d] Lower Bound	95% Confidence Interval for Difference[d] Upper Bound
1	0	1	11,866[*,b]	,920	<,001	10,045	13,687
	1	0	-11,866[*,c]	,920	<,001	-13,687	-10,045
2	0	1	12,887[*,b]	1,003	<,001	10,903	14,872
	1	0	-12,887[*,c]	1,003	<,001	-14,872	-10,903
3	0	1	13,274[*,b,c]	,881	<,001	11,531	15,017
	1	0	-13,274[*,b,c]	,881	<,001	-15,017	-11,531
4	0	1	14,102[*,b,c]	,967	<,001	12,190	16,015
	1	0	-14,102[*,b,c]	,967	<,001	-16,015	-12,190

Based on estimated marginal means

*. The mean difference is significant at the ,05 level.

b. An estimate of the modified population marginal mean (J).

c. An estimate of the modified population marginal mean (I).

d. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable: GOT_min

Load_Quartile		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
1	Contrast	875,628	1	875,628	166,202	<,001	,563
	Error	679,629	129	5,268			
2	Contrast	869,802	1	869,802	165,097	<,001	,561
	Error	679,629	129	5,268			
3	Contrast	1196,284	1	1196,284	227,066	<,001	,638
	Error	679,629	129	5,268			
4	Contrast	1121,243	1	1121,243	212,823	<,001	,623
	Error	679,629	129	5,268			

Each F tests the simple effects of BRMS_Enabled within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

2. BRMS_Enabled * Load_Quartile

Estimates

Dependent Variable: GOT_min

BRMS_Enabled	Load_Quartile	Mean	Std. Error	95% Confidence Interval	
				Lower Bound	Upper Bound
0	1	57,397[a]	1,042	55,334	59,459
	2	57,225[a]	,737	55,767	58,683
	3	58,489[a,b]	,740	57,026	59,953
	4	58,755[a,b]	1,080	56,618	60,892
1	1	45,531[a,b]	1,157	43,242	47,820
	2	44,338[a,b]	,696	42,962	45,714
	3	45,215[a,b]	,597	44,034	46,396
	4	44,653[a,b]	1,022	42,632	46,675

a. Covariates appearing in the model are evaluated at the following values: Passenger_Count = 142,01.

b. Based on modified population marginal mean.

Pairwise Comparisons

Dependent Variable: GOT_min

BRMS_Enabled	(I) Load_Quartile	(J) Load_Quartile	Mean Difference (I-J)	Std. Error	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	Upper Bound
0	1	2	,172	1,197	1,000	-3,035	3,379
		3	-1,092[a]	1,419	1,000	-4,895	2,710
		4	-1,358[a]	1,904	1,000	-6,460	3,744
	2	1	-,172	1,197	1,000	-3,379	3,035
		3	-1,264[a]	1,067	1,000	-4,123	1,595
		4	-1,530[a]	1,372	1,000	-5,207	2,148
	3	1	1,092[b]	1,419	1,000	-2,710	4,895
		2	1,264[b]	1,067	1,000	-1,595	4,123
		4	-,266[a,b]	1,174	1,000	-3,411	2,879
	4	1	1,358[b]	1,904	1,000	-3,744	6,460
		2	1,530[b]	1,372	1,000	-2,148	5,207
		3	,266[a,b]	1,174	1,000	-2,879	3,411
1	1	2	1,193[a,b]	1,287	1,000	-2,255	4,641
		3	,316[a,b]	1,491	1,000	-3,678	4,310
		4	,878[a,b]	1,962	1,000	-4,379	6,135
	2	1	-1,193[a,b]	1,287	1,000	-4,641	2,255
		3	-,877[a,b]	,946	1,000	-3,411	1,658
		3	-1,264[a]	1,067	1,000	-4,123	1,595
		4	-1,530[a]	1,372	1,000	-5,207	2,148
	3	1	1,092[b]	1,419	1,000	-2,710	4,895
		2	1,264[b]	1,067	1,000	-1,595	4,123
		4	-,266[a,b]	1,174	1,000	-3,411	2,879
	4	1	1,358[b]	1,904	1,000	-3,744	6,460
		2	1,530[b]	1,372	1,000	-2,148	5,207
		3	,266[a,b]	1,174	1,000	-2,879	3,411
1	1	2	1,193[a,b]	1,287	1,000	-2,255	4,641
		3	,316[a,b]	1,491	1,000	-3,678	4,310
		4	,878[a,b]	1,962	1,000	-4,379	6,135
	2	1	-1,193[a,b]	1,287	1,000	-4,641	2,255
		3	-,877[a,b]	,946	1,000	-3,411	1,658
		4	-,315[a,b]	1,296	1,000	-3,788	3,158
	3	1	-,316[a,b]	1,491	1,000	-4,310	3,678
		2	,877[a,b]	,946	1,000	-1,658	3,411
		4	,562[a,b]	,958	1,000	-2,004	3,128
	4	1	-,878[a,b]	1,962	1,000	-6,135	4,379
		2	,315[a,b]	1,296	1,000	-3,158	3,788
		3	-,562[a,b]	,958	1,000	-3,128	2,004

Based on estimated marginal means

a. An estimate of the modified population marginal mean (J).

b. An estimate of the modified population marginal mean (I).

c. Adjustment for multiple comparisons: Bonferroni.

Univariate Tests

Dependent Variable: GOT_min

BRMS_Enabled		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
0	Contrast	8,953	3	2,984	,566	,638	,013
	Error	679,629	129	5,268			
1	Contrast	8,348	3	2,783	,528	,664	,012
	Error	679,629	129	5,268			

Each F tests the simple effects of Load_Quartile within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

RANK

Created Variables[a]

Source Variable	Function	New Variable	Label
Passenger_Count[b]	Rank	RAN003	Rank of Passenger_Count
	Percentile Group[c]	NTI003	Percentile Group of Passenger_Count

a. Mean rank of tied values is used for ties.

b. Ranks are in ascending order.

c. 4 groups are generated.

```
SAVE OUTFILE='C:\Users\moheblu\Documents\DEC2025\20251208_MHD_BRMS_Study_170flights_48strata.sav'
  /COMPRESSED.
FREQUENCIES VARIABLES=Load_Quartile
  /ORDER=ANALYSIS.
```

Statistics

Load_Quartile

N	Valid	171
	Missing	0

Load_Quartile

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	43	25,1	25,1	25,1
	2	43	25,1	25,1	50,3
	3	43	25,1	25,1	75,4
	4	42	24,6	24,6	100,0
	Total	171	100,0	100,0	

```
MEANS TABLES=GOT_min BY Load_Quartile BRMS_Enabled
  /CELLS=MEAN COUNT STDDEV.
```

Means

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
GOT_min * Load_Quartile	171	100,0%	0	0,0%	171	100,0%
GOT_min * BRMS_Enabled	171	100,0%	0	0,0%	171	100,0%

GOT_min * Load_Quartile

GOT_min

Load_Quartile	Mean	N	Std. Deviation
1	48,53	43	6,599
2	50,00	43	7,121
3	50,91	43	6,686
4	52,33	42	7,459
Total	50,43	171	7,047

GOT_min * BRMS_Enabled

GOT_min

BRMS_Enabled	Mean	N	Std. Deviation
0	57,74	74	3,638
1	44,86	97	2,291
Total	50,43	171	7,047

Appendix C.6: FastBoard and FastDeboard logistic regression (S1-H6a/S1-H6b)

Logistic Regression

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	171	100,0
	Missing Cases	0	,0
	Total	171	100,0
Unselected Cases		0	,0
Total		171	100,0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Categorical Variables Codings

			Parameter coding		
		Frequency	(1)	(2)	(3)
Gate_Type	1	32	,000	,000	,000
	2	53	1,000	,000	,000
	3	59	,000	1,000	,000
	4	27	,000	,000	1,000
Shared_Access_Points	1	49	,000	,000	
	2	84	1,000	,000	
	3	38	,000	1,000	
Time_of_Day	1	66	,000	,000	
	2	53	1,000	,000	
	3	52	,000	1,000	
Self_Checkin_Used	0	69	,000		
	1	102	1,000		
Day_Type	0	142	,000		
	1	29	1,000		
Flight_Type	0	111	,000		
	1	60	1,000		
BRMS_Enabled	0	74	,000		
	1	97	1,000		

Block 0: Beginning Block

Classification Table[a,b]

Observed			Predicted FastBoard_hit 0	Predicted FastBoard_hit 1	Percentage Correct
Step 0	FastBoard_hit	0	0	74	,0
		1	0	97	100,0
	Overall Percentage				56,7

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	,271	,154	3,075	1	,080	1,311

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Passenger_Count	92,006	1	<,001
		Flights_per_Gate_per_Day	,830	1	,362
		BRMS_Enabled(1)	4,724	1	,030
		Gate_Type	1,204	3	,752
		Gate_Type(1)	,417	1	,518
		Gate_Type(2)	,023	1	,879
		Gate_Type(3)	,961	1	,327
		Time_of_Day	3,193	2	,203
		Time_of_Day(1)	1,725	1	,189
		Time_of_Day(2)	,254	1	,614
		Day_Type(1)	1,100	1	,294
		Flight_Type(1)	12,737	1	<,001
		Shared_Access_Points	1,744	2	,418
		Shared_Access_Points(1)	,527	1	,468
		Shared_Access_Points(2)	1,742	1	,187
		Self_Checkin_Used(1)	14,588	1	<,001
	Overall Statistics		117,216	13	<,001

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	231,181	13	<,001
	Block	231,181	13	<,001
	Model	231,181	13	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	2,773[a]	,741	,994

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	,000	4	1,000

Contingency Table for Hosmer and Lemeshow Test

		FastBoard_hit = 0		FastBoard_hit = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	17	17,000	0	,000	17
	2	17	17,000	0	,000	17
	3	17	17,000	0	,000	17
	4	17	17,000	0	,000	17
	5	6	6,000	11	11,000	17
	6	0	,000	86	86,000	86

Classification Table[a]

			Predicted		
			FastBoard_hit		Percentage Correct
	Observed		0	1	
Step 1	FastBoard_hit	0	73	1	98,6
		1	0	97	100,0
	Overall Percentage				99,4

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Passenger_Count	-4,658	128,378	,001	1	,971	,009	,000	1,789E+107
	Flights_per_Gate_per_Day	-17,358	972,417	,000	1	,986	,000	,000	.
	BRMS_Enabled(1)	53,451	10502,655	,000	1	,996	1,634E+23	,000	.
	Gate_Type			,000	3	1,000			
	Gate_Type(1)	11,550	23163,412	,000	1	1,000	103747,762	,000	.
	Gate_Type(2)	14,790	23167,286	,000	1	,999	2649223,282	,000	.
	Gate_Type(3)	-18,687	25112,323	,000	1	,999	,000	,000	.
	Time_of_Day			,001	2	1,000			
	Time_of_Day(1)	-48,977	1810,907	,001	1	,978	,000	,000	.
	Time_of_Day(2)	-34,155	3804,481	,000	1	,993	,000	,000	.
	Day_Type(1)	45,087	3606,967	,000	1	,990	3,810E+19	,000	.
	Flight_Type(1)	-30,866	1316,655	,001	1	,981	,000	,000	.
	Shared_Access_Points			,000	2	1,000			
	Shared_Access_Points(1)	15,978	23180,893	,000	1	,999	8689189,071	,000	.
	Shared_Access_Points(2)	61,609	23470,492	,000	1	,998	5,709E+26	,000	.
	Self_Checkin_Used(1)	136,633	10919,844	,000	1	,990	2,181E+59	,000	.
	Constant	766,305	22839,376	,001	1	,973	.		

a. Variable(s) entered on step 1: Passenger_Count, Flights_per_Gate_per_Day, BRMS_Enabled, Gate_Type, Time_of_Day, Day_Type, Flight_Type, Shared_Access_Points, Self_Checkin_Used.

Logistic Regression

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	171	100,0
	Missing Cases	0	,0
	Total	171	100,0
Unselected Cases		0	,0
Total		171	100,0

a. If weight is in effect, see classification table for the total number of cases.

Dependent Variable Encoding

Original Value	Internal Value
0	0
1	1

Categorical Variables Codings

			Parameter coding		
		Frequency	(1)	(2)	(3)
Gate_Type	1	32	,000	,000	,000
	2	53	1,000	,000	,000
	3	59	,000	1,000	,000
	4	27	,000	,000	1,000
Shared_Access_Points	1	49	,000	,000	
	2	84	1,000	,000	
	3	38	,000	1,000	
Time_of_Day	1	66	,000	,000	
	2	53	1,000	,000	
	3	52	,000	1,000	
Self_Checkin_Used	0	69	,000		
	1	102	1,000		
Day_Type	0	142	,000		
	1	29	1,000		
Flight_Type	0	111	,000		
	1	60	1,000		
BRMS_Enabled	0	74	,000		
	1	97	1,000		

Classification Table[a,b]

			Predicted		
			FastDeboard_hit		Percentage Correct
	Observed		0	1	
Step 0	FastDeboard_hit	0	99	0	100,0
		1	72	0	,0
	Overall Percentage				57,9

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	-,318	,155	4,227	1	,040	,727

Variables not in the Equation

			Score	df	Sig.
Step 0	Variables	Passenger_Count	111,944	1	<,001
		Flights_per_Gate_per_Day	,118	1	,732
		BRMS_Enabled(1)	1,690	1	,194
		Gate_Type	,376	3	,945
		Gate_Type(1)	,011	1	,916
		Gate_Type(2)	,075	1	,784
		Gate_Type(3)	,024	1	,876
		Time_of_Day	6,660	2	,036
		Time_of_Day(1)	6,623	1	,010
		Time_of_Day(2)	1,720	1	,190
		Day_Type(1)	,008	1	,931
		Flight_Type(1)	13,362	1	<,001
		Shared_Access_Points	,573	2	,751
		Shared_Access_Points(1)	,256	1	,613
		Shared_Access_Points(2)	,555	1	,456
		Self_Checkin_Used(1)	,110	1	,740
	Overall Statistics		118,050	13	<,001

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	232,775	13	<,001
	Block	232,775	13	<,001
	Model	232,775	13	<,001

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	,000[a]	,744	1,000

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	,000	5	1,000

Contingency Table for Hosmer and Lemeshow Test

		FastDeboard_hit = 0		FastDeboard_hit = 1		
		Observed	Expected	Observed	Expected	Total
Step 1	1	29	29,000	0	,000	29
	2	17	17,000	0	,000	17
	3	17	17,000	0	,000	17
	4	17	17,000	0	,000	17
	5	17	17,000	0	,000	17
	6	2	2,000	10	10,000	12
	7	0	,000	62	62,000	62

Classification Table[a]

			Predicted		
			FastDeboard_hit		Percentage
	Observed		0	1	Correct
Step 1	FastDeboard_hit	0	99	0	100,0
		1	0	72	100,0
	Overall Percentage				100,0

a. The cut value is ,500

Variables in the Equation

								95% C.I.for EXP(B)	
		B	S.E.	Wald	df	Sig.	Exp(B)	Lower	Upper
Step 1[a]	Passenger_Count	-14,199	172,128	,007	1	,934	,000	,000	2,232E+140
	Flights_per_Gate_per_Day	-1,214	497,545	,000	1	,998	,297	,000	.
	BRMS_Enabled(1)	314,254	3829,922	,007	1	,935	3,012E+136	,000	.
	Gate_Type			,000	3	1,000			
	Gate_Type(1)	63,257	13007,183	,000	1	,996	2,967E+27	,000	.
	Gate_Type(2)	214,563	18728,173	,000	1	,991	1,525E+93	,000	.
	Gate_Type(3)	70,040	54460,102	,000	1	,999	2,617E+30	,000	.
	Time_of_Day			,005	2	,997			
	Time_of_Day(1)	-33,992	696,274	,002	1	,961	,000	,000	.
	Time_of_Day(2)	72,968	1076,954	,005	1	,946	4,892E+31	,000	.
	Day_Type(1)	133,522	47419,089	,000	1	,998	9,726E+57	,000	.
	Flight_Type(1)	-167,861	2132,268	,006	1	,937	,000	,000	.
	Shared_Access_Points			,000	2	1,000			
	Shared_Access_Points(1)	47,438	12959,429	,000	1	,997	4,001E+20	,000	.
	Shared_Access_Points(2)	190,750	18586,501	,000	1	,992	6,942E+82	,000	.
	Self_Checkin_Used(1)	-25,000	701,718	,001	1	,972	,000	,000	.
	Constant	1682,178	20747,603	,007	1	,935	.		

a. Variable(s) entered on step 1: Passenger_Count, Flights_per_Gate_per_Day, BRMS_Enabled, Gate_Type, Time_of_Day, Day_Type, Flight_Type, Shared_Access_Points, Self_Checkin_Used.

Correlation Matrix 1

	Const.	Pax_Ct	Flt/Gate	BRMS	Gate(1)	Gate(2)	Gate(3)	ToD(1)	ToD(2)	Day(1)	Flt_Tp(1)	SAP(1)	SAP(2)	SelfCk
Constant	1.000	-.928	-.727	.168	.015	.018	.052	-.678	-.432	.145	-.592	.013	.053	.221
Passenger_Count	-.928	1.000	.443	-.205	-.020	-.017	-.046	.658	.466	-.184	.556	-.010	-.081	-.236
Flights_per_Gate	-.727	.443	1.000	-.019	.024	.012	.019	.497	.005	-.242	.474	-.047	.081	-.187
BRMS_Enabled(1)	.168	-.205	-.019	1.000	.002	.002	.019	-.120	-.157	.012	-.048	-.008	.000	-.867
Gate_Type(1)	.015	-.020	.024	.002	1.000	.998	.954	.015	-.116	.176	.014	-.997	-.990	-.021
Gate_Type(2)	.018	-.017	.012	.002	.998	1.000	.954	.012	-.111	.176	.008	-.997	-.990	-.019
Gate_Type(3)	.052	-.046	.019	.019	.954	.954	1.000	.051	-.340	-.319	.016	-.955	-.968	-.086
Time_of_Day(1)	-.678	.658	.497	-.120	.015	.012	.051	1.000	.141	-.332	.705	-.029	-.070	-.237
Time_of_Day(2)	-.432	.466	.005	-.157	-.116	-.111	-.340	.141	1.000	.438	-.028	.120	.140	.099
Day_Type(1)	.145	-.184	-.242	.012	.176	.176	-.319	-.332	.438	1.000	-.282	.086	.140	.260
Flight_Type(1)	-.592	.556	.474	-.048	.014	.008	.016	.705	-.028	-.282	1.000	.040	-.994	.035
Shared_Access(1)	.013	-.010	-.047	-.008	-.997	-.997	-.955	-.029	.120	.086	.040	1.000	.994	.061
Shared_Access(2)	.053	-.081	.081	.000	-.990	-.990	-.968	-.070	.140	.140	-.994	.994	1.000	.061
Self_Checkin_Used	.221	-.236	-.187	-.867	-.021	-.019	-.086	-.237	.099	.260	.035	.061	.061	1.000

Correlation Matrix 2

	Const.	Pax_Ct	Flt/Gate	BRMS	Gate(1)	Gate(2)	Gate(3)	ToD(1)	ToD(2)	Day(1)	Flt_Tp(1)	SAP(1)	SAP(2)	SelfCk
Constant	1.000	-.972	-.229	.977	.066	.150	.022	-.688	.833	.036	-.952	.030	.109	-.415
Passenger_Count	-.972	1.000	-.003	-.984	-.078	-.162	-.027	.597	-.879	-.034	.977	-.030	-.104	.380
Flights_per_Gate	-.229	-.003	1.000	-.074	.037	.031	.019	.446	.064	-.012	.012	.007	-.038	.130
BRMS_Enabled(1)	.977	-.984	-.074	1.000	.071	.156	.025	-.632	.833	.034	-.956	.029	.104	-.496
Gate_Type(1)	.066	-.078	.037	.071	1.000	.703	.240	-.027	.070	-.150	-.073	-.992	-.964	-.017
Gate_Type(2)	.150	-.162	.031	.156	.703	1.000	.475	-.081	.136	-.023	-.152	-.687	-.687	-.053
Gate_Type(3)	.022	-.027	.019	.025	.240	.475	1.000	-.006	.017	-.006	-.023	-.237	-.471	-.009
Time_of_Day(1)	-.688	.597	.446	-.632	-.027	-.081	-.006	1.000	-.425	-.027	.609	-.021	-.085	.272
Time_of_Day(2)	.833	-.879	.064	.833	.070	.136	.017	-.425	1.000	.033	-.830	.120	.161	-.280
Day_Type(1)	.036	-.034	-.012	.034	-.150	-.023	-.006	-.027	.033	1.000	-.035	.001	.001	-.010
Flight_Type(1)	-.952	.977	.012	-.956	-.073	-.152	-.023	.609	-.830	-.035	1.000	.035	.111	-.011
Shared_Access(1)	.030	-.030	.007	.029	-.992	-.687	-.237	-.021	.120	.001	.035	1.000	.701	.011
Shared_Access(2)	.109	-.104	-.038	.104	-.964	-.687	-.471	-.085	.161	.001	.111	.701	1.000	-.036
Self_Checkin_Used	-.415	.380	.130	-.496	-.017	-.053	-.009	.272	-.280	-.010	-.011	.011	-.036	1.000

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	171	100,0
	Missing Cases	0	,0
	Total	171	100,0
Unselected Cases		0	,0
Total		171	100,0

a. If weight is in effect, see classification table for the total number of cases.

```
DATASET ACTIVATE DataSet1.

SAVE OUTFILE='C:\Users\moheblu\Documents\DEC2025\20251208_MHD_BRMS_Study_170flights_48strata.sav'
  /COMPRESSED.
FREQUENCIES VARIABLES=FastBoard_hit FastDeboard_hit OnTimeTurn_hit
  /ORDER=ANALYSIS.
```

Frequencies

Statistics

		FastBoard_hit	FastDeboard_hit	OnTimeTurn_hit
N	Valid	171	171	171
	Missing	0	0	0

Frequency Table

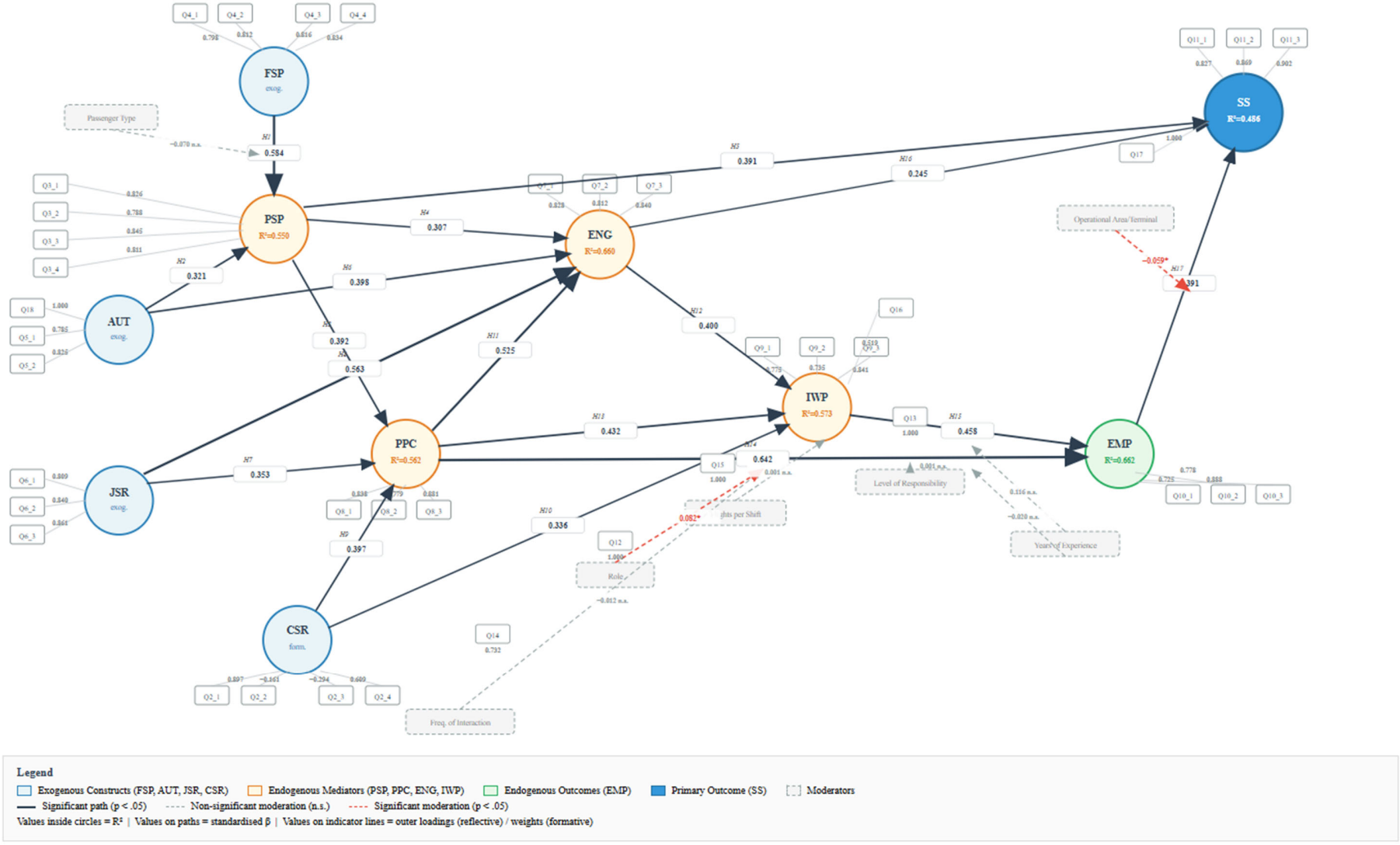
FastBoard_hit

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	74	43,3	43,3	43,3
	1	97	56,7	56,7	100,0
	Total	171	100,0	100,0	

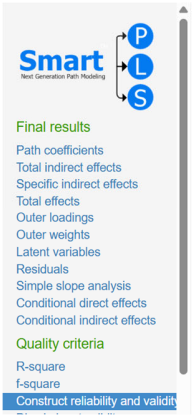
FastDeboard_hit

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	99	57,9	57,9	57,9
	1	72	42,1	42,1	100,0
	Total	171	100,0	100,0	

Appendix D.1: PLS Algorithm - Path Model Diagram



Appendix D.2: Construct Reliability and Validity



Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AUT	0.777	0.785	0.871	0.692
EMP	0.718	0.746	0.842	0.641
ENG	0.768	0.769	0.866	0.683
FSP	0.841	0.847	0.893	0.677
IWP	0.701	0.709	0.833	0.626
JSR	0.787	0.788	0.876	0.701
PPC	0.760	0.768	0.862	0.677
PSP	0.832	0.832	0.888	0.665
SS	0.833	0.835	0.900	0.751

Construct reliability and validity charts

Appendix D.3: Outer Loadings

Indicator	AUT	CSR	EMP	ENG	FSP	FpS	IWP	IntFreq	JSR	LvlResp	OpArea	PPC	PSP	PassType	Role	SS	YrsExp	PassT×FSP	IntF×PPC	LvlR×PPC	LvlR×EMP	YrsE×IWP	OpA×EMP	Role×PPC	FpS×IWP
Q5_1	0.785																								
Q5_2	0.825																								
Q5_3	0.884																								
Q2_1		0.801																							
Q2_2		0.585																							
Q2_3		0.698																							
Q2_4		0.815																							
Q10_1			0.728																						
Q10_2			0.778																						
Q10_3			0.888																						
Q7_1				0.828																					
Q7_2				0.812																					
Q7_3				0.840																					
Q3_1					0.826																				
Q3_2					0.786																				
Q3_3					0.846																				
Q3_4					0.831																				
Q15						1.000																			
Q9_1							0.775																		
Q9_2							0.755																		
Q9_3							0.841																		
Q14								1.000																	
Q6_1									0.809																
Q6_2									0.840																
Q6_3									0.863																
Q16										1.000															
Q17											1.000														
Q8_1												0.779													
Q8_2												0.804													
Q8_3												0.881													
Q4_1													0.798												
Q4_2													0.812												
Q4_3													0.816												
Q4_4													0.834												
Q18														1.000											
Q12															1.000										
Q11_1																0.827									
Q11_2																0.869									
Q11_3																0.902									
Q13																	1.000								
PassType × FSP																		1.000							
IntFreq × PPC																			1.000						
LvlResp × PPC																				1.000					
LvlResp × EMP																					1.000				
YrsExp × IWP																						1.000			
OpArea × EMP																							1.000		
Role × PPC																								1.000	
FpS × IWP																									1.000

Relationship	Loading	Type	Threshold
Reflective Constructs (← indicators reflect the construct)			
Q5_1 ← AUT	0.785	Reflective	✓ > 0.708
Q5_2 ← AUT	0.825	Reflective	✓ > 0.708
Q5_3 ← AUT	0.884	Reflective	✓ > 0.708
Q2_1 ← CSR	0.801	Formative	—
Q2_2 ← CSR	0.585	Formative	—
Q2_3 ← CSR	0.698	Formative	—
Q2_4 ← CSR	0.815	Formative	—
Q10_1 ← EMP	0.728	Reflective	✓ > 0.708
Q10_2 ← EMP	0.778	Reflective	✓ > 0.708
Q10_3 ← EMP	0.888	Reflective	✓ > 0.708
Q7_1 ← ENG	0.828	Reflective	✓ > 0.708
Q7_2 ← ENG	0.812	Reflective	✓ > 0.708
Q7_3 ← ENG	0.840	Reflective	✓ > 0.708
Q3_1 ← FSP	0.826	Reflective	✓ > 0.708
Q3_2 ← FSP	0.786	Reflective	✓ > 0.708
Q3_3 ← FSP	0.846	Reflective	✓ > 0.708
Q3_4 ← FSP	0.831	Reflective	✓ > 0.708
Q9_1 ← IWP	0.775	Reflective	✓ > 0.708
Q9_2 ← IWP	0.755	Reflective	✓ > 0.708
Q9_3 ← IWP	0.841	Reflective	✓ > 0.708
Q6_1 ← JSR	0.809	Reflective	✓ > 0.708
Q6_2 ← JSR	0.840	Reflective	✓ > 0.708
Q6_3 ← JSR	0.863	Reflective	✓ > 0.708
Q8_1 ← PPC	0.779	Reflective	✓ > 0.708
Q8_2 ← PPC	0.804	Reflective	✓ > 0.708
Q8_3 ← PPC	0.881	Reflective	✓ > 0.708
Q4_1 ← PSP	0.798	Reflective	✓ > 0.708
Q4_2 ← PSP	0.812	Reflective	✓ > 0.708
Q4_3 ← PSP	0.816	Reflective	✓ > 0.708
Q4_4 ← PSP	0.834	Reflective	✓ > 0.708
Q11_1 ← SS	0.827	Reflective	✓ > 0.708
Q11_2 ← SS	0.869	Reflective	✓ > 0.708
Q11_3 ← SS	0.902	Reflective	✓ > 0.708

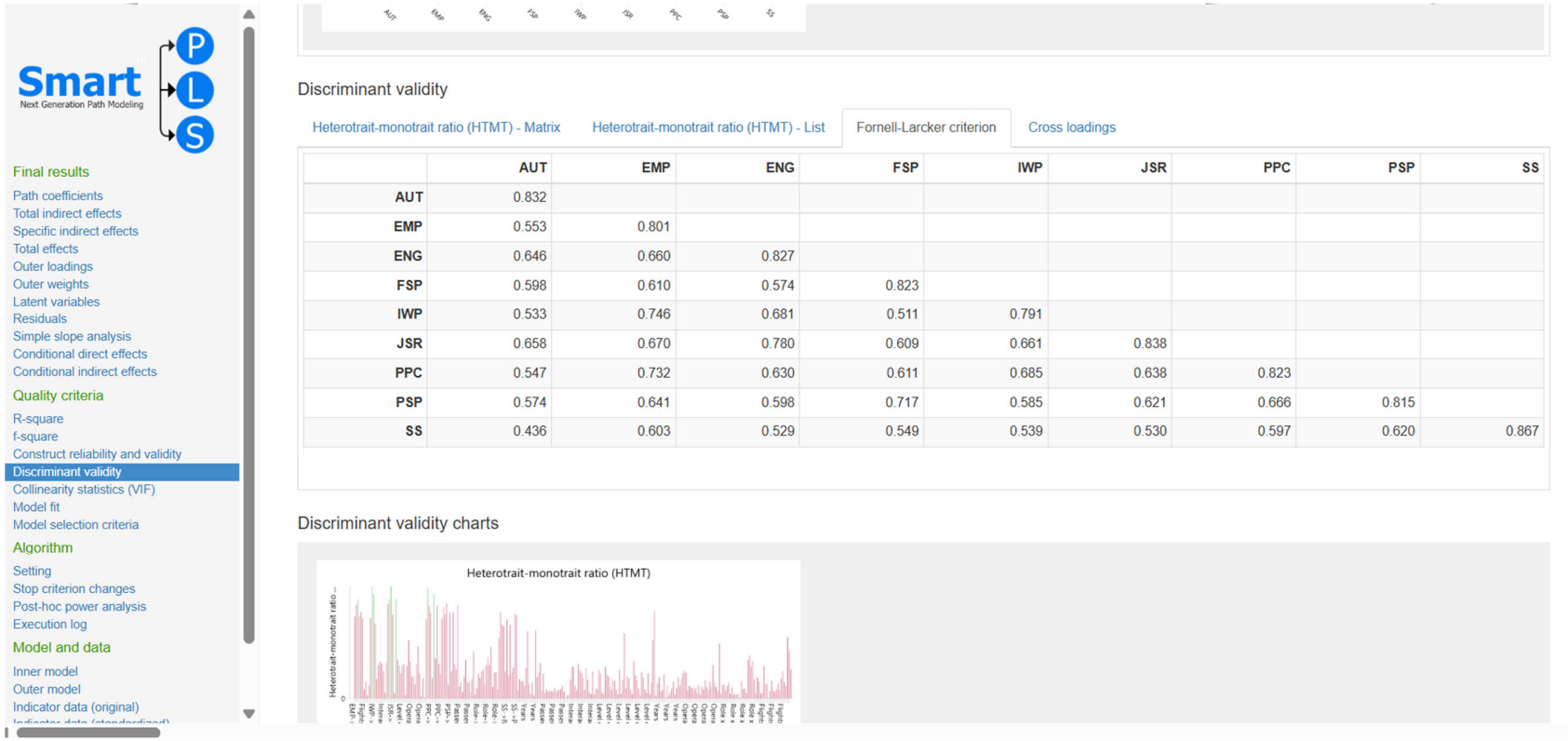
Relationship	Loading	Type	Note
Single-Indicator Formative Constructs (⟶ indicator defines the construct)			
Q12 ⟶ Role	1.000	Formative	Single item
Q13 ⟶ Years of Experience	1.000	Formative	Single item
Q14 ⟶ InteractionFrequency	1.000	Formative	Single item
Q15 ⟶ FlightsPerShift	1.000	Formative	Single item
Q16 ⟶ Level of Responsibility	1.000	Formative	Single item
Q17 ⟶ Operational Area / Terminal	1.000	Formative	Single item
Q18 ⟶ Passenger Type	1.000	Formative	Single item

Relationship	Loading	Type	Note
Moderation Product Terms (two-stage approach)			
Passenger Type × FSP ⟶ Passenger Type × FSP	1.000	Product term	Two-stage
InteractionFrequency × PPC ⟶ InteractionFrequency × PPC	1.000	Product term	Two-stage
Level of Responsibility × PPC ⟶ Level of Responsibility × PPC	1.000	Product term	Two-stage
Level of Responsibility × EMP ⟶ Level of Responsibility × EMP	1.000	Product term	Two-stage
Years of Experience × IWP ⟶ Years of Experience × IWP	1.000	Product term	Two-stage
Operational Area / Terminal × EMP ⟶ Operational Area / Terminal × EMP	1.000	Product term	Two-stage
Role × PPC ⟶ Role × PPC	1.000	Product term	Two-stage
FlightsPerShift × IWP ⟶ FlightsPerShift × IWP	1.000	Product term	Two-stage

Appendix D.4: Outer Weights - Formative Construct (FSP)

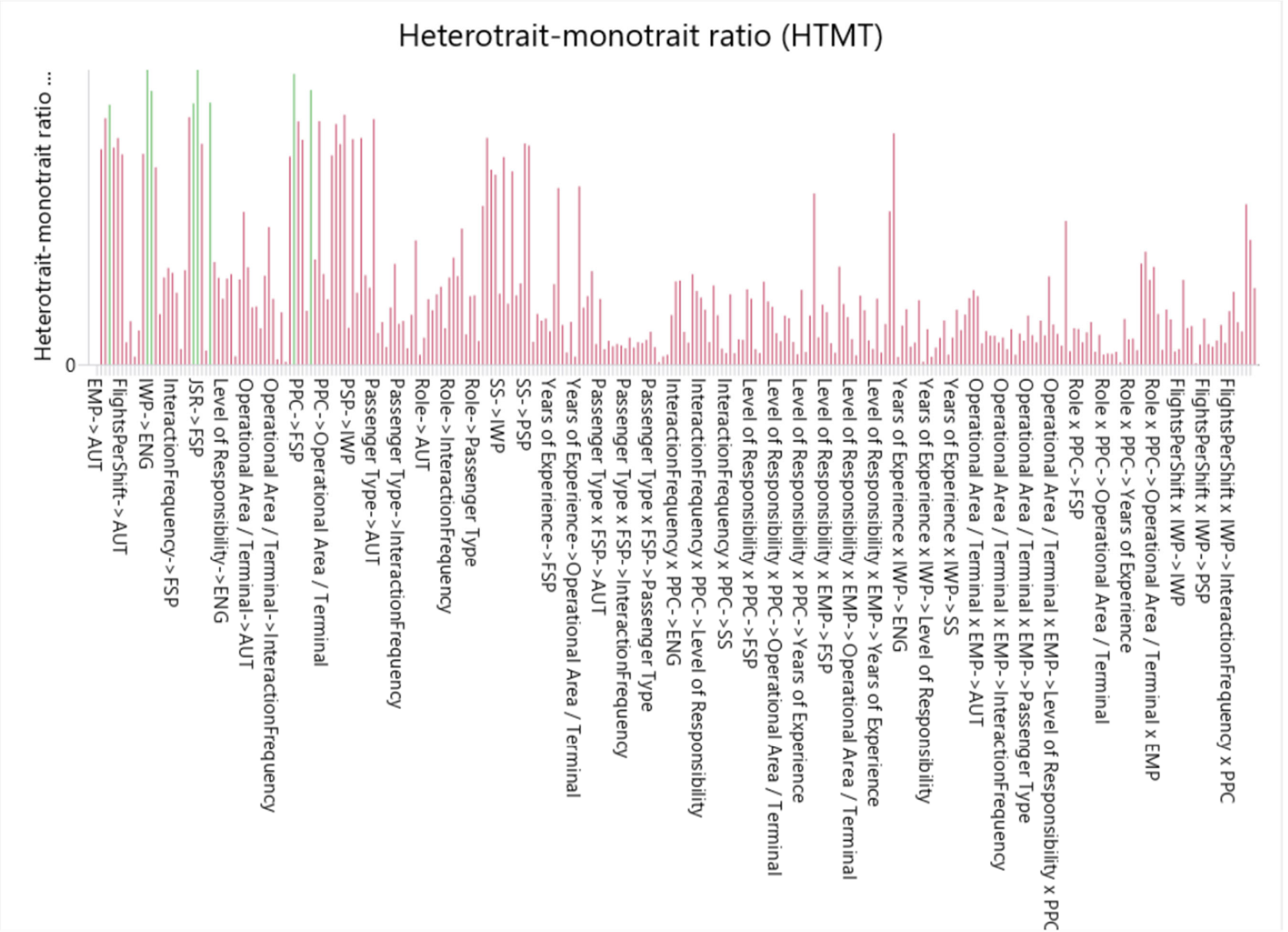
Indicator	AUT	CSR	EMP	ENG	FSP	FpS	IWP	IntFreq	JSR	LvlResp	OpArea	PPC	PSP	PassType	Role	SS	YrsExp	PassTÂ—FSP	IntFÂ—PPC	LvlRÂ—PPC	LvlRÂ—EMP	YrsEÂ—IWP	OpAÂ—EMP	RoleÂ—PPC	FpSÂ—IWP
Q5_1	0.367																								
Q5_2	0.398																								
Q5_3	0.435																								
Q2_1		0.397																							
Q2_2		0.161																							
Q2_3		0.294																							
Q2_4		0.469																							
Q10_1			0.360																						
Q10_2			0.391																						
Q10_3			0.489																						
Q7_1				0.399																					
Q7_2				0.396																					
Q7_3				0.415																					
Q3_1					0.353																				
Q3_2					0.281																				
Q3_3					0.291																				
Q3_4					0.290																				
Q15						1.000																			
Q9_1							0.404																		
Q9_2							0.391																		
Q9_3							0.466																		
Q14								1.000																	
Q6_1									0.390																
Q6_2									0.397																
Q6_3									0.406																
Q16										1.000															
Q17											1.000														
Q8_1												0.378													
Q8_2												0.394													
Q8_3												0.441													
Q4_1													0.321												
Q4_2													0.307												
Q4_3													0.289												
Q4_4													0.310												
Q18														1.000											
Q12															1.000										
Q11_1																0.371									
Q11_2																0.386									
Q11_3																0.397									
Q13																	1.000								
PassType x FSP																		1.000							
IntFreq x PPC																			1.000						
LvlResp x PPC																				1.000					
LvlResp x EMP																					1.000				
YrsExp x IWP																						1.000			
OpArea x EMP																							1.000		
Role x PPC																								1.000	
FpS x IWP																									1.000

Appendix D.5: Discriminant Validity - Fornell-Larcker Criterion



	AUT	EMP	ENG	FSP	IWP	JSR	PPC	PSP	SS
AUT	0.832								
EMP	0.553	0.801							
ENG	0.646	0.660	0.827						
FSP	0.598	0.610	0.574	0.823					
IWP	0.533	0.746	0.681	0.511	0.791				
JSR	0.658	0.670	0.780	0.609	0.661	0.838			
PPC	0.547	0.732	0.630	0.611	0.685	0.638	0.823		
PSP	0.574	0.641	0.598	0.717	0.585	0.621	0.666	0.815	
SS	0.436	0.603	0.529	0.549	0.539	0.530	0.597	0.620	0.867

Appendix D.6: Discriminant Validity - HTMT Ratios



Heterotrait-monotrait ratio (HTMT) - Matrix

Construct	AUT	EMP	ENG	FSP	FpS	IWP	IntFreq	JSR	LvlResp	OpArea	PPC	PSP	PassType	Role	SS	YrsExp	PassT×FSP	IntF×PPC	LvlR×PPC	LvlR×EMP	YrsE×IWP	OpA×EMP	Role×PPC	FpS×IWP
AUT																								
EMP	0.731																							
ENG	0.836	**0.882**																						
FSP	0.736	0.769	0.713																					
FpS	0.075	0.147	0.026	0.115																				
IWP	0.715	**1.042**	**0.929**	0.669	0.171																			
IntFreq	0.295	0.328	0.311	0.243	0.052	0.320																		
JSR	0.840	**0.887**	**1.004**	0.749	0.047	**0.889**	0.347																	
LvlResp	0.294	0.223	0.291	0.306	0.028	0.288	0.518	0.330																
OpArea	0.194	0.196	0.122	0.301	0.466	0.223	0.017	0.177	0.009															
PPC	0.706	**0.986**	0.825	0.763	0.182	**0.932**	0.356	0.826	0.307	0.221														
PSP	0.710	0.816	0.748	0.848	0.124	0.765	0.243	0.769	0.303	0.261	0.833													
PassType	0.107	0.144	0.059	0.193	0.341	0.138	0.147	0.055	0.168	0.421	0.032	0.091												
Role	0.221	0.184	0.238	0.264	0.123	0.295	0.362	0.300	0.461	0.102	0.231	0.235	0.079											
SS	0.538	0.769	0.661	0.644	0.240	0.704	0.206	0.655	0.235	0.275	0.750	0.743	0.077	0.171										
YrsExp	0.148	0.156	0.112	0.273	0.599	0.134	0.041	0.144	0.026	0.605	0.193	0.232	0.316	0.069	0.222									
PassT×FSP	0.052	0.080	0.061	0.069	0.064	0.055	0.091	0.057	0.075	0.073	0.083	0.111	0.059	0.007	0.027	0.033								
IntF×PPC	0.167	0.282	0.285	0.110	0.074	0.306	0.249	0.227	0.185	0.076	0.268	0.167	0.053	0.039	0.238	0.038	0.085							
LvlR×PPC	0.083	0.255	0.223	0.052	0.039	0.281	0.214	0.196	0.106	0.079	0.166	0.157	0.076	0.035	0.253	0.042	0.166	0.581						
LvlR×EMP	0.092	0.203	0.177	0.072	0.040	0.332	0.205	0.161	0.086	0.031	0.233	0.184	0.081	0.052	0.223	0.040	0.137	0.520	0.785					
YrsE×IWP	0.025	0.132	0.187	0.060	0.074	0.218	0.010	0.119	0.026	0.057	0.090	0.149	0.033	0.091	0.185	0.116	0.169	0.225	0.252	0.232				
OpA×EMP	0.072	0.113	0.098	0.097	0.074	0.091	0.052	0.120	0.033	0.105	0.080	0.166	0.099	0.075	0.149	0.099	0.299	0.135	0.104	0.064	0.487			
Role×PPC	0.045	0.123	0.120	0.075	0.109	0.144	0.043	0.100	0.033	0.037	0.036	0.043	0.007	0.154	0.085	0.087	0.048	0.343	0.383	0.287	0.331	0.171		
FpS×IWP	0.049	0.186	0.153	0.044	0.052	0.287	0.124	0.130	0.004	0.067	0.156	0.069	0.060	0.081	0.134	0.073	0.181	0.246	0.143	0.112	0.544	0.423	0.259	

Appendix D.7: Discriminant Validity - Cross-Loadings

Indicator	AUT	CSR	EMP	ENG	FSP	FpS	IWP	IntFreq	JSR	LvlResp	OpArea	PPC	PSP	PassType	Role	SS	YrsExp	PassT×FSP	IntF×PPC	LvlR×PPC	LvlR×EMP	YrsE×IWP	OpA×EMP	Role×PPC	FpS×IWP
Q10_1 (EMP)	0.386	0.415	**0.728**	0.483	0.403	0.045	0.523	-0.214	0.472	-0.133	0.116	0.535	0.392	0.096	-0.218	0.399	0.076	0.089	0.185	0.159	0.127	0.007	-0.024	0.059	-0.122
Q10_2 (EMP)	0.420	0.396	**0.778**	0.468	0.431	0.146	0.569	-0.212	0.506	-0.190	0.159	0.557	0.497	0.099	-0.034	0.437	0.104	-0.040	0.152	0.183	0.147	-0.089	-0.094	0.020	-0.061
Q10_3 (EMP)	0.511	0.485	**0.888**	0.619	0.607	0.106	0.686	-0.240	0.620	-0.130	0.125	0.659	0.626	0.097	-0.122	0.591	0.136	-0.034	0.236	0.176	0.138	-0.172	-0.111	0.170	-0.195
Q11_1 (SS)	0.360	0.379	0.508	0.460	0.436	0.166	0.463	-0.096	0.475	-0.190	0.210	0.548	0.504	0.012	-0.162	**0.827**	0.234	0.023	0.163	0.245	0.190	-0.155	-0.170	0.055	-0.091
Q11_2 (SS)	0.340	0.412	0.512	0.424	0.506	0.181	0.453	-0.224	0.406	-0.232	0.207	0.486	0.561	0.065	-0.147	**0.869**	0.123	0.024	0.153	0.130	0.141	-0.126	-0.070	0.018	-0.097
Q11_3 (SS)	0.432	0.460	0.547	0.490	0.484	0.223	0.485	-0.169	0.497	-0.134	0.236	0.519	0.546	0.105	-0.097	**0.902**	0.169	0.017	0.249	0.225	0.198	-0.158	-0.113	0.129	-0.130
Q12 (Role)	-0.195	-0.211	-0.151	-0.209	-0.240	-0.123	-0.246	0.362	-0.266	0.461	-0.102	-0.200	-0.213	-0.079	**1.000**	-0.155	-0.069	-0.007	-0.039	-0.035	-0.052	0.091	0.075	-0.154	0.081
Q13 (YrsExp)	0.131	0.230	0.134	0.099	0.253	0.599	0.107	0.041	0.128	-0.026	0.605	0.165	0.210	0.316	-0.069	0.202	**1.000**	-0.033	0.038	0.042	-0.040	-0.116	-0.099	0.087	-0.073
Q14 (IntFreq)	-0.256	-0.268	-0.277	-0.273	-0.227	0.052	-0.271	**1.000**	-0.308	0.518	-0.017	-0.311	-0.223	0.147	0.362	-0.189	0.041	-0.091	-0.249	-0.214	-0.205	0.010	0.052	-0.043	0.124
Q15 (FpS)	0.069	0.172	0.125	0.023	0.107	**1.000**	0.141	0.052	0.042	-0.028	0.466	0.158	0.114	0.341	-0.123	0.220	0.599	0.064	0.074	0.039	-0.040	-0.074	-0.074	0.109	-0.052
Q16 (LvlResp)	-0.259	-0.209	-0.186	-0.256	-0.278	-0.028	-0.244	0.518	-0.293	**1.000**	-0.009	-0.266	-0.278	0.168	0.461	-0.213	-0.026	-0.075	-0.185	-0.106	-0.086	0.026	0.033	-0.033	0.004
Q17 (OpArea)	0.175	0.278	0.165	0.107	0.277	0.466	0.184	-0.017	0.158	-0.009	**1.000**	0.192	0.237	0.421	-0.102	0.251	0.605	0.073	0.076	0.079	0.031	-0.057	0.105	0.037	-0.067
Q18 (PassType)	0.086	0.118	0.121	0.004	0.175	0.341	0.113	0.147	0.049	0.168	0.421	0.027	0.082	**1.000**	-0.079	0.071	0.316	0.059	-0.053	-0.076	-0.081	0.033	0.099	-0.007	0.060
Q2_1 (CSR)	0.460	**0.801**	0.440	0.455	0.511	0.232	0.434	-0.200	0.454	-0.174	0.246	0.475	0.423	0.101	-0.138	0.491	0.203	0.043	0.137	0.127	0.127	-0.094	0.003	0.094	0.015
Q2_2 (CSR)	0.267	**0.585**	0.347	0.358	0.329	0.037	0.300	-0.134	0.333	-0.112	0.126	0.361	0.272	0.039	-0.110	0.273	0.177	0.070	0.080	0.055	0.073	-0.166	0.006	0.074	-0.073
Q2_3 (CSR)	0.467	**0.698**	0.385	0.364	0.427	0.114	0.362	-0.135	0.395	-0.123	0.198	0.427	0.389	0.091	-0.111	0.291	0.088	-0.002	0.022	0.009	0.036	-0.021	0.087	0.011	-0.074
Q2_4 (CSR)	0.436	**0.815**	0.421	0.496	0.429	0.087	0.415	-0.273	0.515	-0.184	0.218	0.506	0.510	0.097	-0.225	0.336	0.202	-0.003	0.058	0.066	0.053	-0.106	-0.053	0.032	-0.068
Q3_1 (FSP)	0.475	0.512	0.552	0.485	**0.826**	0.114	0.402	-0.231	0.491	-0.195	0.245	0.537	0.680	0.115	-0.172	0.586	0.246	-0.050	0.122	0.075	0.091	0.003	-0.084	-0.019	0.058
Q3_2 (FSP)	0.476	0.441	0.465	0.441	**0.786**	0.116	0.458	-0.137	0.449	-0.249	0.256	0.463	0.541	0.222	-0.233	0.410	0.199	-0.009	0.023	0.015	0.033	0.006	0.093	0.041	0.031
Q3_3 (FSP)	0.520	0.464	0.492	0.460	**0.846**	0.114	0.434	-0.190	0.525	-0.215	0.173	0.479	0.560	0.158	-0.194	0.362	0.199	-0.086	0.144	0.042	0.078	-0.085	-0.053	0.108	-0.043
Q3_4 (FSP)	0.499	0.491	0.488	0.501	**0.831**	0.004	0.393	-0.176	0.539	-0.266	0.235	0.523	0.557	0.088	-0.197	0.418	0.179	-0.065	0.044	-0.025	0.015	-0.088	-0.064	0.058	-0.001
Q4_1 (PSP)	0.473	0.476	0.511	0.472	0.639	0.136	0.444	-0.220	0.471	-0.268	0.181	0.570	**0.798**	0.053	-0.170	0.537	0.178	0.046	0.213	0.204	0.223	-0.116	-0.094	0.032	-0.027
Q4_2 (PSP)	0.506	0.469	0.514	0.465	0.566	0.068	0.411	-0.176	0.512	-0.190	0.197	0.542	**0.812**	0.066	-0.084	0.531	0.145	-0.071	0.110	0.076	0.053	0.008	-0.061	-0.038	0.008
Q4_3 (PSP)	0.420	0.423	0.490	0.513	0.558	0.084	0.482	-0.151	0.522	-0.184	0.228	0.474	**0.816**	0.077	-0.230	0.465	0.234	-0.163	0.082	0.102	0.134	-0.184	-0.186	0.035	-0.074
Q4_4 (PSP)	0.471	0.471	0.573	0.499	0.572	0.081	0.570	-0.177	0.523	-0.259	0.169	0.580	**0.834**	0.073	-0.214	0.486	0.133	-0.049	0.091	0.084	0.137	-0.136	-0.152	0.022	-0.097
Q5_1 (AUT)	**0.785**	0.471	0.385	0.516	0.389	0.011	0.399	-0.296	0.489	-0.241	0.029	0.388	0.410	-0.012	-0.154	0.308	0.103	0.051	0.148	0.089	0.067	-0.011	0.045	0.010	-0.044
Q5_2 (AUT)	**0.825**	0.471	0.456	0.530	0.549	0.039	0.452	-0.156	0.531	-0.147	0.225	0.465	0.478	0.160	-0.175	0.346	0.117	-0.015	0.054	0.021	0.036	0.036	0.100	0.048	-0.064
Q5_3 (AUT)	**0.884**	0.478	0.530	0.565	0.544	0.115	0.477	-0.197	0.617	-0.258	0.171	0.505	0.538	0.062	-0.157	0.427	0.106	0.047	0.166	0.073	0.099	-0.008	-0.013	0.040	-0.001
Q6_1 (JSR)	0.574	0.460	0.565	0.625	0.509	0.022	0.531	-0.284	**0.809**	-0.225	0.089	0.543	0.512	0.041	-0.237	0.431	0.106	-0.063	0.198	0.115	0.137	-0.075	-0.138	0.154	-0.118
Q6_2 (JSR)	0.516	0.485	0.535	0.659	0.505	0.047	0.521	-0.222	**0.840**	-0.247	0.115	0.526	0.498	0.003	-0.212	0.456	0.098	0.025	0.194	0.212	0.112	-0.137	-0.065	0.025	-0.099
Q6_3 (JSR)	0.564	0.538	0.584	0.676	0.516	0.036	0.607	-0.268	**0.863**	-0.263	0.189	0.535	0.551	0.078	-0.219	0.445	0.118	-0.039	0.113	0.109	0.109	-0.054	-0.063	0.044	-0.073
Q7_1 (ENG)	0.497	0.489	0.532	**0.828**	0.460	0.017	0.531	-0.215	0.666	-0.222	0.071	0.501	0.480	0.031	-0.226	0.454	0.074	-0.041	0.231	0.182	0.172	-0.113	-0.049	0.108	-0.025
Q7_2 (ENG)	0.540	0.455	0.552	**0.812**	0.497	0.017	0.557	-0.223	0.641	-0.188	0.119	0.502	0.496	0.039	-0.122	0.411	0.058	-0.063	0.167	0.113	0.068	-0.086	-0.006	0.051	-0.098
Q7_3 (ENG)	0.565	0.489	0.552	**0.840**	0.468	0.024	0.600	-0.237	0.629	-0.223	0.076	0.559	0.505	-0.058	-0.170	0.447	0.112	0.030	0.222	0.190	0.145	-0.208	-0.157	0.103	-0.209
Q8_1 (PPC)	0.435	0.414	0.583	0.481	0.491	0.113	0.539	-0.237	0.458	-0.276	0.150	**0.779**	0.501	0.044	-0.229	0.443	0.168	0.120	0.184	0.129	0.172	-0.041	0.068	0.002	-0.075
Q8_2 (PPC)	0.389	0.515	0.534	0.540	0.505	0.150	0.545	-0.242	0.567	-0.149	0.173	**0.804**	0.520	0.026	-0.110	0.501	0.143	-0.042	0.145	0.091	0.138	-0.088	-0.057	-0.071	-0.119
Q8_3 (PPC)	0.519	0.566	0.683	0.535	0.513	0.128	0.603	-0.286	0.548	-0.235	0.152	**0.881**	0.616	0.000	-0.158	0.525	0.104	0.016	0.247	0.136	0.192	-0.064	-0.048	0.004	-0.141
Q9_1 (IWP)	0.396	0.419	0.569	0.489	0.358	0.116	**0.775**	-0.179	0.513	-0.217	0.164	0.543	0.426	0.118	-0.226	0.403	0.107	0.021	0.165	0.160	0.201	-0.162	-0.002	0.091	-0.198
Q9_2 (IWP)	0.351	0.357	0.537	0.565	0.440	0.129	**0.755**	-0.188	0.499	-0.124	0.156	0.438	0.459	0.093	-0.175	0.409	0.140	0.000	0.174	0.155	0.210	-0.102	-0.076	0.065	-0.152
Q9_3 (IWP)	0.507	0.457	0.657	0.565	0.418	0.094	**0.841**	-0.268	0.555	-0.231	0.122	0.630	0.501	0.062	-0.185	0.464	0.019	0.088	0.269	0.243	0.248	-0.168	-0.103	0.129	-0.220
FpS × IWP	-0.042	-0.059	-0.163	-0.135	0.016	-0.052	-0.242	0.124	-0.115	0.004	-0.067	-0.137	-0.058	0.060	0.081	-0.123	-0.073	0.181	-0.246	-0.143	-0.112	0.544	0.423	-0.259	**1.000**
IntFreq × PPC	0.148	0.101	0.241	0.250	0.104	0.074	0.260	-0.249	0.200	-0.185	0.076	0.236	0.154	-0.053	-0.039	0.218	0.038	0.085	**1.000**	0.581	0.520	-0.225	-0.135	0.343	-0.246
LvlResp × EMP	0.082	0.098	0.170	0.156	0.068	-0.040	0.279	-0.205	0.142	-0.086	0.031	0.204	0.169	-0.081	-0.052	0.204	-0.040	0.137	0.520	0.785	**1.000**	-0.232	-0.064	0.287	-0.112
LvlResp × PPC	0.073	0.093	0.215	0.196	0.036	0.039	0.239	-0.214	0.173	-0.106	0.079	0.145	0.144	-0.076	-0.035	0.230	0.042	0.166	0.581	**1.000**	0.785	-0.252	-0.104	0.383	-0.143
OpArea × EMP	0.050	0.003	-0.100	-0.087	-0.038	-0.074	-0.078	0.052	-0.105	0.033	0.105	-0.018	-0.150	0.099	0.075	-0.135	-0.099	0.299	-0.135	-0.104	-0.064	0.487	**1.000**	-0.171	0.423
PassType × FSP	0.033	0.027	0.000	-0.028	-0.064	0.064	0.049	-0.091	-0.030	-0.075	0.073	0.036	-0.070	0.059	-0.007	0.025	-0.033	**1.000**	0.085	0.166	0.137	0.169	0.299	0.048	0.181
Role × PPC	0.040	0.068	0.112	0.106	0.053	0.109	0.122	-0.043	0.088	-0.033	0.037	-0.026	0.016	-0.007	-0.154	0.079	0.087	0.048	0.343	0.383	0.287	-0.331	-0.171	**1.000**	-0.259
YrsExp × IWP	0.007	-0.120	-0.116	-0.165	-0.048	-0.074	-0.184	0.010	-0.106	0.026	-0.057	-0.079	-0.130	0.033	0.091	-0.169	-0.116	0.169	-0.225	-0.252	-0.232	**1.000**	0.487	-0.331	0.544

Appendix D.8: Collinearity Statistics (VIF)

Outer model - List | Inner model - Matrix | Inner model - List

AUT -> ENG	
AUT -> PSP	
CSR -> IWP	
CSR -> PPC	
EMP -> SS	
ENG -> IWP	
ENG -> SS	
FlightsPerShift -> EMP	
FlightsPerShift x IWP -> EMP	
FSP -> PSP	
InteractionFrequency -> EMP	
InteractionFrequency x PPC -> EMP	
IWP -> EMP	
IWP -> SS	
JSR -> ENG	
JSR -> PPC	
Level of Responsibility -> EMP	
Level of Responsibility -> SS	
Level of Responsibility x EMP -> SS	
Level of Responsibility x PPC -> EMP	
Operational Area / Terminal -> SS	
Operational Area / Terminal x EMP -> SS	
Passenger Type -> PSP	
Passenger Type x FSP -> PSP	
PPC -> EMP	
PPC -> ENG	
PPC -> IWP	
PSP -> ENG	
PSP -> PPC	
PSP -> SS	
Role -> EMP	
Role x PPC -> EMP	
Years of Experience -> EMP	
Years of Experience x IWP -> EMP	

Appendix D.9: Collinearity Statistics (VIF)

D.4a: Outer VIF (1/3)

Indicator	VIF
Q5_1 (AUT)	1.490
Q5_2 (AUT)	1.632
Q5_3 (AUT)	1.922
Q2_1 (CSR)	1.484
Q2_2 (CSR)	1.275
Q2_3 (CSR)	1.347
Q2_4 (CSR)	1.387
Q10_1 (EMP)	1.338
Q10_2 (EMP)	1.462
Q10_3 (EMP)	1.758
Q7_1 (ENG)	1.591
Q7_2 (ENG)	1.508
Q7_3 (ENG)	1.615
Q3_1 (FSP)	1.711
Q3_2 (FSP)	1.677
Q3_3 (FSP)	2.126

D.4a: Outer VIF (2/3)

Indicator	VIF
Q3_4 (FSP)	2.005
Q9_1 (IWP)	1.356
Q9_2 (IWP)	1.315
Q9_3 (IWP)	1.480
Q6_1 (JSR)	1.512
Q6_2 (JSR)	1.704
Q6_3 (JSR)	1.834
Q8_1 (PPC)	1.457
Q8_2 (PPC)	1.543
Q8_3 (PPC)	1.864
Q4_1 (PSP)	1.634
Q4_2 (PSP)	1.757
Q4_3 (PSP)	1.882
Q4_4 (PSP)	1.964
Q11_1 (SS)	1.686
Q11_2 (SS)	2.092

D.4a: Outer VIF (3/3)

Indicator	VIF
Q11_3 (SS)	2.409
Q12 (Role)	1.000
Q13 (YrsExp)	1.000
Q14 (IntFreq)	1.000
Q15 (FpS)	1.000
Q16 (LvlResp)	1.000
Q17 (OpArea)	1.000
Q18 (PassType)	1.000
FpS × IWP	1.000
IntFreq × PPC	1.000
LvlResp × EMP	1.000
LvlResp × PPC	1.000
OpArea × EMP	1.000
PassType × FSP	1.000
Role × PPC	1.000
YrsExp × IWP	1.000

D.4b: Model Fit

Criterion	Saturated	Estimated
SRMR	0.050	0.062
d_ULS	2.040	3.159
d_G	1.071	1.144
Chi-square	1,308.733	1,333.765
NFI	0.742	0.738

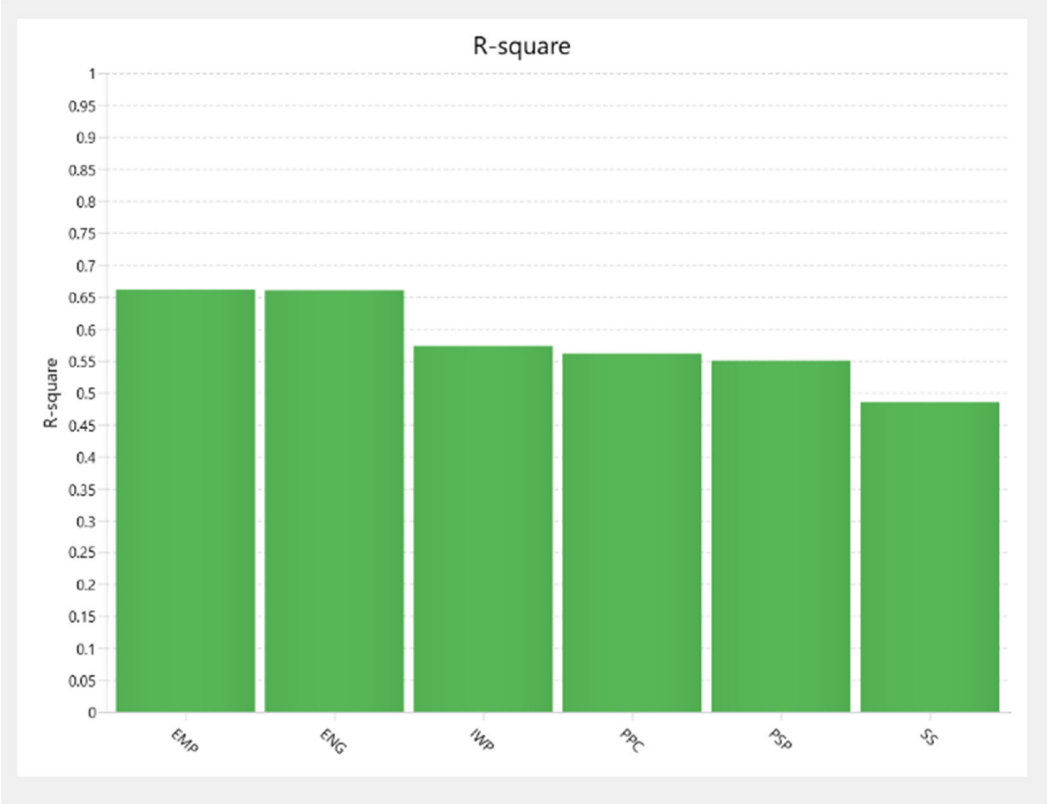
D.4c: BIC (Model Selection)

Construct	BIC
EMP	−171.393
ENG	−213.801
IWP	−168.462
PPC	−162.464
PSP	−151.358
SS	−100.004

Appendix D.10: R-Square Values

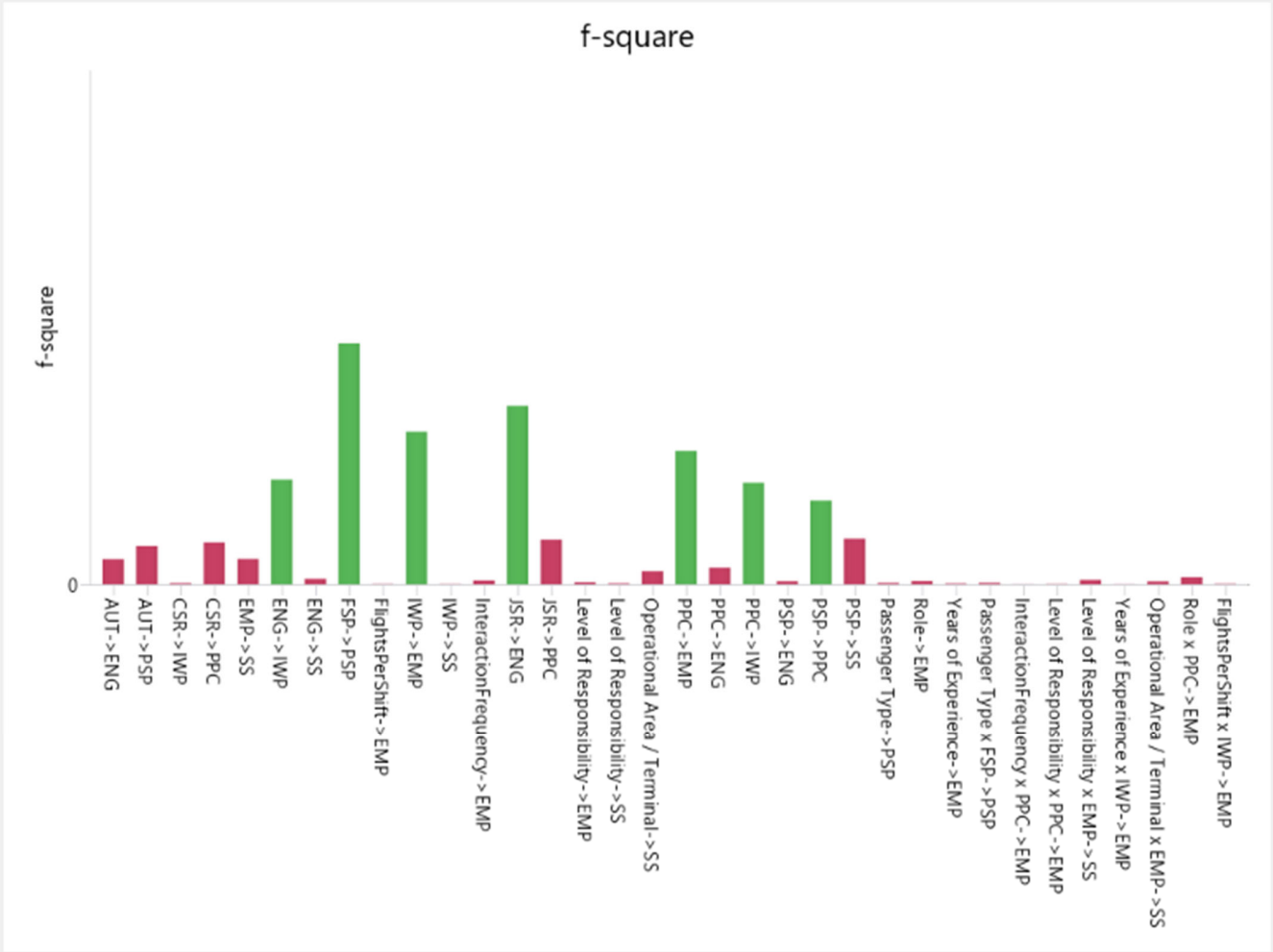
	R-square	R-square adjusted
EMP	0,662	0,642
ENG	0,660	0,654
IWP	0,573	0,567
PPC	0,562	0,556
PSP	0,550	0,542
SS	0,486	0,466

R-square Chart



Appendix D.11: f-Square Effect Sizes

Predictor	EMP	ENG	IWP	PPC	PSP	SS
AUT		0.049		0.075		
CSR			0.002		0.082	
EMP						0.050
ENG			0.204			0.011
FSP					0.469	
FlightsPerShift		0.001				
IWP				0.297		0.001
InteractionFrequency		0.008				
JSR		0.347		0.087		
Level of Responsibility		0.005				0.002
Operational Area / Terminal						0.026
PPC	0.260	0.033			0.198	
PSP		0.006		0.163		0.089
Passenger Type					0.003	
Role		0.007				
SS						
Years of Experience		0.002				
Passenger Type × FSP					0.003	
InteractionFrequency × PPC		0.000				
Level of Resp. × PPC		0.001				
Level of Resp. × EMP						0.009
Years of Exp. × IWP		0.000				
Op. Area × EMP						0.006
Role × PPC		0.015				
FlightsPerShift × IWP		0.001				


f-square
f-square
0
AUT->ENG
AUT->PSP
CSR->IWP
CSR->PPC
EMP->SS
ENG->IWP
ENG->SS
FSP->PSP
FlightsPerShift->EMP
IWP->EMP
IWP->SS
InteractionFrequency->EMP
JSR->ENG
JSR->PPC
Level of Responsibility->EMP
Level of Responsibility->SS
Operational Area / Terminal->SS
PPC->EMP
PPC->ENG
PPC->IWP
PSP->ENG
PSP->PPC
PSP->SS
Passenger Type->PSP
Role->EMP
Years of Experience->EMP
Passenger Type x FSP->PSP
InteractionFrequency x PPC->EMP
Level of Responsibility x PPC->EMP
Level of Responsibility x EMP->SS
Years of Experience x IWP->EMP
Operational Area / Terminal x EMP->SS
Role x PPC->EMP
FlightsPerShift x IWP->EMP

STUDY2 Bootstrapping

Appendix D.12: Bootstrapping - Path Coefficients

Path	O	M	SD	T	p	Sig.
AUT → ENG	**0.180**	0.184	0.078	2.317	**0.021**	✓ p < 0.05
AUT → PSP	**0.230**	0.236	0.072	3.210	**0.001**	✓ p < 0.01
CSR → IWP	0.043	0.049	0.075	0.573	0.567	n.s.
CSR → PPC	**0.248**	0.250	0.076	3.246	**0.001**	✓ p < 0.01
EMP → SS	**0.267**	0.272	0.094	2.847	**0.004**	✓ p < 0.01
ENG → IWP	**0.400**	0.400	0.073	5.473	**0.000**	✓ p < 0.001
ENG → SS	0.112	0.113	0.076	1.476	0.140	n.s.
FlightsPerShift → EMP	−0.020	−0.013	0.050	0.401	0.689	n.s.
FpS × IWP → EMP	0.023	0.021	0.062	0.366	0.714	n.s.
FSP → PSP	**0.584**	0.578	0.065	8.955	**0.000**	✓ p < 0.001
IntFreq → EMP	−0.065	−0.064	0.050	1.307	0.191	n.s.
IntFreq × PPC → EMP	−0.012	−0.011	0.047	0.263	0.793	n.s.
IWP → EMP	**0.458**	0.460	0.058	7.918	**0.000**	✓ p < 0.001
IWP → SS	0.030	0.029	0.131	0.229	0.819	n.s.
JSR → ENG	**0.521**	0.515	0.081	6.410	**0.000**	✓ p < 0.001
JSR → PPC	**0.269**	0.269	0.090	2.999	**0.003**	✓ p < 0.01
LvlResp → EMP	0.050	0.051	0.049	1.013	0.311	n.s.
LvlResp → SS	−0.034	−0.032	0.054	0.625	0.532	n.s.
LvlResp × EMP → SS	0.068	0.068	0.051	1.347	0.178	n.s.
LvlResp × PPC → EMP	0.020	0.017	0.058	0.354	0.723	n.s.
OpArea → SS	**0.121**	0.117	0.050	2.416	**0.016**	✓ p < 0.05
OpArea × EMP → SS	−0.059	−0.053	0.056	1.048	0.295	n.s.
PassType → PSP	−0.037	−0.037	0.045	0.824	0.410	n.s.
PassType × FSP → PSP	−0.038	−0.038	0.047	0.806	0.420	n.s.
PPC → EMP	**0.428**	0.432	0.057	7.472	**0.000**	✓ p < 0.001
PPC → ENG	**0.154**	0.157	0.076	2.021	**0.043**	✓ p < 0.05
PPC → IWP	**0.406**	0.402	0.093	4.360	**0.000**	✓ p < 0.001
PSP → ENG	0.068	0.066	0.076	0.885	0.376	n.s.
PSP → PPC	**0.359**	0.360	0.082	4.388	**0.000**	✓ p < 0.001
PSP → SS	**0.306**	0.304	0.084	3.659	**0.000**	✓ p < 0.001
Role → EMP	0.057	0.056	0.042	1.350	0.177	n.s.
Role × PPC → EMP	0.082	0.083	0.045	1.833	0.067	n.s. (p = 0.067)
YrsExp → EMP	0.031	0.028	0.056	0.547	0.584	n.s.
YrsExp × IWP → EMP	0.014	0.015	0.066	0.210	0.834	n.s.

Appendix D.13: Bootstrapping - Total Effects

Path	O	M	SD	T	p	Sig.
AUT → EMP	**0.089**	0.092	0.030	2.971	**0.003**	✓ **
AUT → ENG	0.028	0.030	0.021	1.375	0.169	n.s.
AUT → IWP	**0.117**	0.119	0.039	2.999	**0.003**	✓ **
AUT → PPC	**0.083**	0.086	0.036	2.292	**0.022**	✓ *
AUT → SS	**0.121**	0.123	0.038	3.170	**0.002**	✓ **
CSR → EMP	**0.179**	0.183	0.056	3.214	**0.001**	✓ **
CSR → ENG	0.038	0.039	0.022	1.756	0.079	n.s.
CSR → IWP	**0.116**	0.116	0.042	2.751	**0.006**	✓ **
CSR → SS	**0.057**	0.058	0.024	2.373	**0.018**	✓ *
ENG → EMP	**0.184**	0.186	0.047	3.944	**0.000**	✓ ***
ENG → SS	0.061	0.060	0.045	1.352	0.176	n.s.
FpS → SS	−0.005	−0.003	0.014	0.375	0.708	n.s.
FpS×IWP → SS	0.006	0.006	0.018	0.334	0.739	n.s.
FSP → EMP	**0.142**	0.140	0.031	4.651	**0.000**	✓ ***
FSP → ENG	0.072	0.071	0.042	1.727	0.084	n.s.
FSP → IWP	**0.114**	0.111	0.028	4.133	**0.000**	✓ ***
FSP → PPC	**0.210**	0.207	0.048	4.381	**0.000**	✓ ***
FSP → SS	**0.228**	0.227	0.049	4.663	**0.000**	✓ ***
IntFreq → SS	−0.017	−0.017	0.015	1.188	0.235	n.s.
IntFreq×PPC → SS	−0.003	−0.003	0.014	0.243	0.808	n.s.
IWP → SS	**0.122**	0.125	0.048	2.568	**0.010**	✓ *
JSR → EMP	**0.268**	0.270	0.066	4.040	**0.000**	✓ ***
JSR → ENG	0.041	0.044	0.029	1.432	0.152	n.s.
JSR → IWP	**0.334**	0.334	0.067	5.014	**0.000**	✓ ***
JSR → SS	**0.145**	0.149	0.056	2.586	**0.010**	✓ *
LvlResp → SS	0.013	0.013	0.014	0.916	0.360	n.s.
LvlResp×PPC → SS	0.005	0.005	0.017	0.326	0.744	n.s.
PassType → EMP	−0.009	−0.009	0.012	0.783	0.434	n.s.
PassType → ENG	−0.005	−0.005	0.007	0.655	0.512	n.s.
PassType → IWP	−0.007	−0.007	0.009	0.789	0.430	n.s.
PassType → PPC	−0.013	−0.013	0.017	0.783	0.434	n.s.
PassType → SS	−0.015	−0.015	0.018	0.796	0.426	n.s.
PassType×FSP → EMP	−0.009	−0.009	0.012	0.799	0.424	n.s.
PassType×FSP → ENG	−0.005	−0.005	0.007	0.656	0.512	n.s.
PassType×FSP → IWP	−0.007	−0.007	0.009	0.797	0.425	n.s.
PassType×FSP → PPC	−0.014	−0.013	0.017	0.796	0.426	n.s.
PassType×FSP → SS	−0.015	−0.015	0.019	0.795	0.427	n.s.
PPC → EMP	**0.214**	0.214	0.048	4.488	**0.000**	✓ ***
PPC → IWP	0.062	0.063	0.034	1.846	0.065	n.s.
PPC → SS	**0.203**	0.213	0.056	3.634	**0.000**	✓ ***
PSP → EMP	**0.243**	0.244	0.052	4.711	**0.000**	✓ ***
PSP → ENG	0.055	0.057	0.031	1.769	0.077	n.s.
PSP → IWP	**0.195**	0.193	0.046	4.223	**0.000**	✓ ***
PSP → SS	**0.084**	0.089	0.026	3.208	**0.001**	✓ **
Role → SS	0.015	0.016	0.014	1.106	0.269	n.s.
Role×PPC → SS	0.022	0.022	0.015	1.492	0.136	n.s.
YrsExp → SS	0.008	0.007	0.016	0.504	0.614	n.s.
YrsExp×IWP → SS	0.004	0.003	0.019	0.197	0.844	n.s.

Appendix D.14: Bootstrapping - Specific Indirect Effects

Source: SmartPLS 4 Bootstrapping. Green = significant ($p < 0.05$). Grey = not significant.

Indirect Path	O	M	SD	T	p	Sig.
JSR → PPC → EMP → SS	**0.031**	0.031	0.015	2.003	**0.045**	*
PassT×FSP → PSP → PPC → IWP → EMP	−0.003	−0.002	0.003	0.770	0.441	n.s.
Role×PPC → EMP → SS	0.022	0.022	0.015	1.492	0.136	n.s.
PassT×FSP → PSP → ENG → IWP → EMP	−0.000	−0.000	0.001	0.439	0.661	n.s.
PPC → ENG → IWP	0.062	0.063	0.034	1.846	0.065	n.s.
AUT → PSP → PPC → EMP → SS	0.009	0.010	0.006	1.485	0.138	n.s.
PSP → ENG → IWP → SS	0.001	0.000	0.006	0.147	0.883	n.s.
PassT×FSP → PSP → PPC → IWP → SS	−0.000	−0.000	0.001	0.143	0.886	n.s.
PPC → ENG → SS	0.017	0.019	0.017	1.035	0.301	n.s.
PassT×FSP → PSP → ENG → IWP → SS	−0.000	−0.000	0.000	0.092	0.927	n.s.
PSP → PPC → IWP → SS	0.004	0.006	0.020	0.222	0.824	n.s.
JSR → PPC → ENG → SS	0.005	0.005	0.006	0.842	0.400	n.s.
PassT×FSP → PSP → PPC → IWP	−0.006	−0.005	0.007	0.784	0.433	n.s.
PassT×FSP → PSP → PPC → ENG	−0.002	−0.002	0.003	0.667	0.505	n.s.
PassT×FSP → PSP → PPC → EMP	−0.006	−0.006	0.007	0.783	0.433	n.s.
PassType → PSP → PPC → ENG → SS	−0.000	−0.000	0.000	0.506	0.613	n.s.
PassT×FSP → PSP → ENG → IWP	−0.001	−0.001	0.002	0.455	0.649	n.s.
IWP → EMP → SS	**0.122**	0.125	0.048	2.568	**0.010**	*
JSR → PPC → ENG → IWP	0.017	0.018	0.012	1.344	0.179	n.s.
FSP → PSP → PPC → ENG → IWP	0.013	0.013	0.008	1.709	0.088	n.s.
AUT → ENG → IWP → EMP → SS	0.009	0.009	0.006	1.441	0.150	n.s.
AUT → PSP → PPC → ENG → IWP → EMP → SS	0.001	0.001	0.001	0.973	0.331	n.s.
Role → EMP → SS	0.015	0.016	0.014	1.106	0.269	n.s.
FSP → PSP → PPC → ENG → SS	0.004	0.004	0.003	1.056	0.291	n.s.
IntFreq×PPC → EMP → SS	−0.003	−0.003	0.014	0.243	0.808	n.s.
PassType → PSP → PPC → ENG → IWP	−0.001	−0.001	0.001	0.669	0.503	n.s.
FSP → PSP → PPC → ENG → IWP → EMP → SS	0.002	0.002	0.001	1.218	0.223	n.s.
PassType → PSP → PPC → ENG → IWP → SS	−0.000	−0.000	0.000	0.128	0.898	n.s.
PassType → PSP → PPC → EMP → SS	−0.002	−0.002	0.002	0.654	0.513	n.s.
PPC → ENG → IWP → EMP → SS	0.008	0.008	0.006	1.302	0.193	n.s.
PassT×FSP → PSP → PPC → IWP → EMP → SS	−0.001	−0.001	0.001	0.717	0.474	n.s.
FSP → PSP → PPC → EMP → SS	**0.024**	0.025	0.012	2.018	**0.044**	*
PassT×FSP → PSP → ENG → SS	−0.000	−0.000	0.001	0.336	0.737	n.s.
ENG → IWP → EMP	**0.184**	0.186	0.047	3.944	**0.000**	***
PassT×FSP → PSP → PPC → ENG → IWP → EMP → SS	−0.000	−0.000	0.000	0.528	0.598	n.s.
PassT×FSP → PSP → ENG → IWP → EMP → SS	−0.000	−0.000	0.000	0.428	0.668	n.s.
FSP → PSP → ENG → SS	0.004	0.005	0.007	0.614	0.539	n.s.
PPC → IWP → EMP	**0.186**	0.185	0.049	3.829	**0.000**	***
PassT×FSP → PSP → PPC → ENG → IWP → EMP	−0.000	−0.000	0.001	0.629	0.529	n.s.
JSR → ENG → IWP → EMP	**0.096**	0.096	0.031	3.060	**0.002**	**
ENG → IWP → SS	0.012	0.009	0.055	0.221	0.825	n.s.
PassT×FSP → PSP → PPC → ENG → IWP → SS	−0.000	−0.000	0.000	0.116	0.907	n.s.
CSR → PPC → ENG → IWP → EMP → SS	0.002	0.002	0.002	1.179	0.238	n.s.
AUT → PSP → PPC → ENG → SS	0.001	0.002	0.002	0.879	0.379	n.s.
FSP → PSP → PPC → EMP	**0.090**	0.090	0.025	3.628	**0.000**	***
FSP → PSP → PPC → ENG	0.032	0.033	0.018	1.828	0.068	n.s.
FpS → EMP → SS	−0.005	−0.003	0.014	0.375	0.708	n.s.
PPC → IWP → SS	0.012	0.017	0.054	0.225	0.822	n.s.
FSP → PSP → PPC → IWP	**0.085**	0.082	0.025	3.350	**0.001**	**
LvlResp → EMP → SS	0.013	0.013	0.014	0.916	0.360	n.s.

CSR → PPC → EMP → SS	**0.028**	0.029	0.014	2.032	**0.042**	*
CSR → PPC → EMP	**0.106**	0.108	0.035	3.004	**0.003**	**
CSR → PPC → ENG	0.038	0.039	0.022	1.756	0.079	n.s.
PPC → IWP → EMP → SS	**0.050**	0.049	0.020	2.522	**0.012**	*
AUT → PSP → PPC → ENG → IWP	0.005	0.005	0.004	1.301	0.193	n.s.
CSR → PPC → IWP	**0.101**	0.101	0.040	2.531	**0.011**	*
FSP → PSP → ENG → IWP	0.016	0.015	0.018	0.865	0.387	n.s.
ENG → IWP → EMP → SS	**0.049**	0.051	0.024	2.044	**0.041**	*
CSR → PPC → ENG → IWP	0.015	0.016	0.010	1.586	0.113	n.s.
YrsExp×IWP → EMP → SS	0.004	0.003	0.019	0.197	0.844	n.s.
AUT → ENG → IWP → SS	0.002	0.001	0.011	0.202	0.840	n.s.
CSR → PPC → ENG → IWP → SS	0.000	0.000	0.003	0.184	0.854	n.s.
PPC → ENG → IWP → EMP	0.028	0.029	0.016	1.751	0.080	n.s.
PassType → PSP → PPC → IWP → EMP → SS	−0.001	−0.001	0.001	0.694	0.488	n.s.
FSP → PSP → PPC → ENG → IWP → SS	0.000	0.000	0.002	0.190	0.849	n.s.
AUT → ENG → IWP → EMP	**0.033**	0.034	0.016	2.003	**0.045**	*
JSR → PPC → ENG → IWP → EMP	0.008	0.008	0.006	1.272	0.203	n.s.
JSR → PPC → IWP → EMP	**0.050**	0.050	0.023	2.199	**0.028**	*
JSR → ENG → IWP → SS	0.006	0.005	0.029	0.218	0.827	n.s.
PassT×FSP → PSP → PPC → EMP → SS	−0.002	−0.001	0.002	0.691	0.490	n.s.
CSR → PPC → ENG → SS	0.004	0.005	0.005	0.922	0.356	n.s.
JSR → PPC → IWP → SS	0.003	0.006	0.016	0.203	0.839	n.s.
AUT → PSP → PPC → IWP → SS	0.001	0.001	0.005	0.199	0.842	n.s.
JSR → PPC → ENG → IWP → EMP → SS	0.002	0.002	0.002	1.044	0.297	n.s.
PSP → PPC → EMP → SS	**0.041**	0.043	0.021	1.988	**0.047**	*
AUT → PSP → PPC → IWP → EMP	**0.015**	0.016	0.008	2.017	**0.044**	*
AUT → PSP → PPC → IWP → EMP → SS	0.004	0.004	0.003	1.601	0.109	n.s.
PassType → PSP → ENG	−0.003	−0.003	0.005	0.460	0.646	n.s.
PassType → PSP → PPC → EMP	−0.006	−0.006	0.008	0.754	0.451	n.s.
AUT → PSP → ENG → IWP → SS	0.000	0.000	0.001	0.132	0.895	n.s.
JSR → PPC → IWP → EMP → SS	0.013	0.013	0.007	1.839	0.066	n.s.
PassT×FSP → PSP → ENG	−0.003	−0.003	0.006	0.464	0.642	n.s.
AUT → PSP → ENG → IWP → EMP	0.003	0.003	0.004	0.754	0.451	n.s.
PassType → PSP → PPC	−0.013	−0.013	0.017	0.783	0.434	n.s.
PassType → PSP → PPC → ENG	−0.002	−0.002	0.003	0.675	0.500	n.s.
AUT → PSP → ENG → IWP → EMP → SS	0.001	0.001	0.001	0.685	0.494	n.s.
PSP → PPC → ENG → IWP → SS	0.001	0.001	0.004	0.185	0.853	n.s.
PassType → PSP → PPC → IWP	−0.005	−0.005	0.007	0.768	0.442	n.s.
PassType → PSP → SS	−0.011	−0.011	0.015	0.782	0.434	n.s.
PassT×FSP → PSP → PPC	−0.014	−0.013	0.017	0.796	0.426	n.s.
JSR → ENG → IWP → EMP → SS	0.025	0.027	0.014	1.813	0.070	n.s.
PSP → PPC → ENG → IWP	0.022	0.023	0.013	1.666	0.096	n.s.
PPC → ENG → IWP → SS	0.002	0.002	0.010	0.190	0.849	n.s.
PassType → PSP → PPC → ENG → IWP → EMP → SS	−0.000	−0.000	0.000	0.566	0.572	n.s.
PassT×FSP → PSP → SS	−0.012	−0.011	0.015	0.780	0.436	n.s.
PassType → PSP → PPC → ENG → IWP → EMP	−0.000	−0.000	0.001	0.671	0.502	n.s.
FSP → PSP → PPC → ENG → IWP → EMP	0.006	0.006	0.004	1.666	0.096	n.s.
YrsExp → EMP → SS	0.008	0.007	0.016	0.504	0.614	n.s.
CSR → IWP → EMP → SS	0.005	0.007	0.010	0.500	0.617	n.s.
JSR → PPC → EMP	**0.115**	0.116	0.040	2.871	**0.004**	**
JSR → PPC → ENG	0.041	0.044	0.029	1.432	0.152	n.s.
PSP → PPC → ENG → SS	0.006	0.006	0.006	1.037	0.300	n.s.
CSR → PPC → IWP → EMP → SS	0.012	0.012	0.006	1.943	0.052	n.s.

AUT → ENG → IWP	**0.072**	0.073	0.033	2.201	**0.028**	*
JSR → PPC → IWP	**0.109**	0.109	0.046	2.378	**0.017**	*
PSP → PPC → EMP	**0.154**	0.156	0.043	3.587	**0.000**	***
PSP → PPC → ENG	0.055	0.057	0.031	1.769	0.077	n.s.
PSP → ENG → IWP → EMP → SS	0.003	0.003	0.004	0.771	0.441	n.s.
FpS×IWP → EMP → SS	0.006	0.006	0.018	0.334	0.739	n.s.
PassType → PSP → PPC → IWP → SS	−0.000	−0.000	0.001	0.140	0.888	n.s.
PSP → PPC → IWP	**0.146**	0.144	0.045	3.275	**0.001**	**
JSR → ENG → IWP	**0.209**	0.207	0.054	3.855	**0.000**	***
AUT → ENG → SS	0.020	0.019	0.015	1.312	0.190	n.s.
PSP → PPC → ENG → IWP → EMP → SS	0.003	0.003	0.002	1.184	0.236	n.s.
PSP → ENG → IWP	0.027	0.026	0.031	0.865	0.387	n.s.
FSP → PSP → ENG → IWP → SS	0.000	0.000	0.003	0.148	0.882	n.s.
JSR → ENG → SS	0.058	0.059	0.041	1.432	0.152	n.s.
AUT → PSP → ENG	0.016	0.016	0.020	0.775	0.439	n.s.
FSP → PSP → PPC → IWP → EMP → SS	**0.010**	0.010	0.005	2.163	**0.031**	*
PassType → PSP → PPC → IWP → EMP	−0.002	−0.002	0.003	0.769	0.442	n.s.
PSP → ENG → SS	0.008	0.009	0.012	0.618	0.536	n.s.
PassType → PSP → ENG → IWP	−0.001	−0.001	0.002	0.460	0.645	n.s.
PassType → PSP → ENG → SS	−0.000	−0.000	0.001	0.342	0.732	n.s.
FSP → PSP → PPC → IWP → SS	0.003	0.003	0.011	0.227	0.821	n.s.
FSP → PSP → ENG	0.039	0.039	0.044	0.886	0.376	n.s.
CSR → IWP → EMP	0.020	0.022	0.034	0.575	0.565	n.s.
FSP → PSP → ENG → IWP → EMP → SS	0.002	0.002	0.002	0.773	0.440	n.s.
PSP → PPC → ENG → IWP → EMP	0.010	0.010	0.006	1.628	0.104	n.s.
PassType → PSP → ENG → IWP → SS	−0.000	−0.000	0.000	0.089	0.929	n.s.
AUT → PSP → PPC	**0.083**	0.086	0.036	2.292	**0.022**	*
AUT → PSP → SS	**0.070**	0.072	0.031	2.243	**0.025**	*
FSP → PSP → PPC	**0.210**	0.207	0.048	4.381	**0.000**	***
JSR → PPC → ENG → IWP → SS	0.001	0.001	0.003	0.164	0.870	n.s.
FSP → PSP → ENG → IWP → EMP	0.007	0.007	0.009	0.850	0.395	n.s.
AUT → PSP → PPC → IWP	**0.034**	0.035	0.017	2.023	**0.043**	*
FSP → PSP → SS	**0.179**	0.176	0.052	3.413	**0.001**	**
PSP → ENG → IWP → EMP	0.012	0.012	0.015	0.851	0.395	n.s.
CSR → IWP → SS	0.001	−0.001	0.011	0.113	0.910	n.s.
CSR → PPC → IWP → EMP	**0.046**	0.046	0.020	2.347	**0.019**	*
AUT → PSP → PPC → EMP	**0.035**	0.038	0.017	2.086	**0.037**	*
AUT → PSP → PPC → ENG	0.013	0.014	0.010	1.333	0.183	n.s.
FSP → PSP → PPC → IWP → EMP	**0.039**	0.038	0.012	3.187	**0.001**	**
PassType → PSP → ENG → IWP → EMP	−0.000	−0.000	0.001	0.462	0.644	n.s.
PSP → PPC → IWP → EMP	**0.067**	0.066	0.021	3.153	**0.002**	**
PassType → PSP → ENG → IWP → EMP → SS	−0.000	−0.000	0.000	0.429	0.668	n.s.
PSP → PPC → IWP → EMP → SS	**0.018**	0.018	0.008	2.132	**0.033**	*
PassT×FSP → PSP → PPC → ENG → SS	−0.000	−0.000	0.000	0.510	0.610	n.s.
CSR → PPC → ENG → IWP → EMP	0.007	0.007	0.005	1.496	0.135	n.s.
IntFreq → EMP → SS	−0.017	−0.017	0.015	1.188	0.235	n.s.
AUT → PSP → PPC → ENG → IWP → EMP	0.002	0.003	0.002	1.285	0.199	n.s.
AUT → PSP → ENG → SS	0.002	0.002	0.003	0.559	0.577	n.s.
PPC → EMP → SS	**0.114**	0.118	0.044	2.590	**0.010**	*
PassT×FSP → PSP → PPC → ENG → IWP	−0.001	−0.001	0.001	0.646	0.518	n.s.
AUT → PSP → PPC → ENG → IWP → SS	0.000	0.000	0.001	0.166	0.868	n.s.
CSR → PPC → IWP → SS	0.003	0.004	0.014	0.213	0.831	n.s.
AUT → PSP → ENG → IWP	0.006	0.006	0.008	0.763	0.446	n.s.
LvlResp×PPC → EMP → SS	0.005	0.005	0.017	0.326	0.744	n.s.

Appendix D.15: Bootstrapping - Outer Loadings Significance

Relationship	O	M	SD	T	p
Reflective Indicators					
Q5_1 ← AUT	**0.785**	0.783	0.032	24.673	**0.000**
Q5_2 ← AUT	**0.825**	0.824	0.026	32.059	**0.000**
Q5_3 ← AUT	**0.884**	0.883	0.014	64.134	**0.000**
Q2_1 → CSR	**0.801**	0.791	0.057	14.131	**0.000**
Q2_2 → CSR	**0.585**	0.576	0.089	6.593	**0.000**
Q2_3 → CSR	**0.698**	0.689	0.070	9.933	**0.000**
Q2_4 → CSR	**0.815**	0.806	0.055	14.885	**0.000**
Q10_1 ← EMP	**0.728**	0.728	0.042	17.150	**0.000**
Q10_2 ← EMP	**0.778**	0.777	0.030	25.616	**0.000**
Q10_3 ← EMP	**0.888**	0.888	0.011	77.371	**0.000**
Q7_1 ← ENG	**0.828**	0.828	0.022	37.386	**0.000**
Q7_2 ← ENG	**0.812**	0.811	0.026	30.932	**0.000**
Q7_3 ← ENG	**0.840**	0.839	0.025	33.727	**0.000**
Q3_1 ← FSP	**0.826**	0.826	0.017	49.002	**0.000**
Q3_2 ← FSP	**0.786**	0.785	0.027	29.490	**0.000**
Q3_3 ← FSP	**0.846**	0.844	0.020	42.363	**0.000**
Q3_4 ← FSP	**0.831**	0.831	0.020	40.680	**0.000**
Q9_1 ← IWP	**0.775**	0.775	0.031	25.001	**0.000**
Q9_2 ← IWP	**0.755**	0.753	0.036	20.684	**0.000**
Q9_3 ← IWP	**0.841**	0.840	0.020	42.631	**0.000**
Q6_1 ← JSR	**0.809**	0.807	0.031	26.271	**0.000**
Q6_2 ← JSR	**0.840**	0.839	0.021	39.600	**0.000**
Q6_3 ← JSR	**0.863**	0.863	0.016	54.372	**0.000**
Q8_1 ← PPC	**0.779**	0.779	0.030	25.951	**0.000**
Q8_2 ← PPC	**0.804**	0.802	0.027	29.460	**0.000**
Q8_3 ← PPC	**0.881**	0.881	0.015	60.732	**0.000**
Q4_1 ← PSP	**0.798**	0.798	0.022	36.000	**0.000**
Q4_2 ← PSP	**0.812**	0.812	0.026	30.759	**0.000**
Q4_3 ← PSP	**0.816**	0.815	0.027	30.136	**0.000**
Q4_4 ← PSP	**0.834**	0.833	0.022	38.370	**0.000**
Q11_1 ← SS	**0.827**	0.826	0.025	33.208	**0.000**
Q11_2 ← SS	**0.869**	0.869	0.020	43.976	**0.000**
Q11_3 ← SS	**0.902**	0.901	0.019	48.641	**0.000**

Relationship	O	M	SD	T	p
Single-Indicator Formative Constructs (loading fixed at 1.000)					
Q12 → Role	1.000	1.000	0.000	n/a	n/a
Q13 → Years of Experience	1.000	1.000	0.000	n/a	n/a
Q14 → InteractionFrequency	1.000	1.000	0.000	n/a	n/a
Q15 → FlightsPerShift	1.000	1.000	0.000	n/a	n/a
Q16 → Level of Responsibility	1.000	1.000	0.000	n/a	n/a
Q17 → Operational Area / Terminal	1.000	1.000	0.000	n/a	n/a
Q18 → Passenger Type	1.000	1.000	0.000	n/a	n/a
Moderation Product Terms (loading fixed at 1.000)					
FpS × IWP → FpS × IWP	1.000	1.000	0.000	n/a	n/a
IntFreq × PPC → IntFreq × PPC	1.000	1.000	0.000	n/a	n/a
LvlResp × EMP → LvlResp × EMP	1.000	1.000	0.000	n/a	n/a
LvlResp × PPC → LvlResp × PPC	1.000	1.000	0.000	n/a	n/a
OpArea × EMP → OpArea × EMP	1.000	1.000	0.000	n/a	n/a
PassType × FSP → PassType × FSP	1.000	1.000	0.000	n/a	n/a
Role × PPC → Role × PPC	1.000	1.000	0.000	n/a	n/a
YrsExp × IWP → YrsExp × IWP	1.000	1.000	0.000	n/a	n/a

Appendix D.16: Bootstrapping - Outer Weights Significance

Relationship	O	M	SD	T	p
Reflective Indicators					
Q5_1 ← AUT	**0.367**	0.366	0.026	14.045	**0.000**
Q5_2 ← AUT	**0.398**	0.399	0.025	16.114	**0.000**
Q5_3 ← AUT	**0.435**	0.435	0.020	22.116	**0.000**
Q2_1 → CSR	**0.397**	0.392	0.104	3.831	**0.000**
Q2_2 → CSR	0.161	0.158	0.107	1.514	0.130
Q2_3 → CSR	**0.294**	0.291	0.098	2.991	**0.000**
Q2_4 → CSR	**0.469**	0.466	0.093	5.018	**0.000**
Q10_1 ← EMP	**0.360**	0.361	0.022	16.214	**0.000**
Q10_2 ← EMP	**0.391**	0.390	0.021	18.188	**0.000**
Q10_3 ← EMP	**0.489**	0.488	0.022	22.364	**0.000**
Q7_1 ← ENG	**0.399**	0.400	0.019	21.000	**0.000**
Q7_2 ← ENG	**0.396**	0.396	0.018	21.997	**0.000**
Q7_3 ← ENG	**0.415**	0.415	0.017	23.836	**0.000**
Q3_1 ← FSP	**0.353**	0.354	0.017	21.211	**0.000**
Q3_2 ← FSP	**0.281**	0.281	0.017	16.433	**0.000**
Q3_3 ← FSP	**0.291**	0.291	0.015	19.909	**0.000**
Q3_4 ← FSP	**0.290**	0.290	0.014	20.061	**0.000**
Q9_1 ← IWP	**0.404**	0.405	0.022	18.173	**0.000**
Q9_2 ← IWP	**0.391**	0.390	0.023	17.018	**0.000**
Q9_3 ← IWP	**0.466**	0.467	0.023	20.593	**0.000**
Q6_1 ← JSR	**0.390**	0.390	0.019	20.652	**0.000**
Q6_2 ← JSR	**0.397**	0.398	0.016	24.508	**0.000**
Q6_3 ← JSR	**0.406**	0.407	0.019	20.889	**0.000**
Q8_1 ← PPC	**0.378**	0.379	0.019	19.525	**0.000**
Q8_2 ← PPC	**0.394**	0.394	0.019	20.945	**0.000**
Q8_3 ← PPC	**0.441**	0.442	0.018	24.933	**0.000**
Q4_1 ← PSP	**0.321**	0.320	0.016	19.527	**0.000**
Q4_2 ← PSP	**0.307**	0.307	0.018	17.252	**0.000**
Q4_3 ← PSP	**0.289**	0.289	0.016	17.885	**0.000**
Q4_4 ← PSP	**0.310**	0.310	0.015	20.205	**0.000**
Q11_1 ← SS	**0.371**	0.371	0.019	19.777	**0.000**
Q11_2 ← SS	**0.386**	0.386	0.018	21.431	**0.000**
Q11_3 ← SS	**0.397**	0.397	0.018	22.155	**0.000**

Relationship	O	M	SD	T	p
Single-Indicator Formative Constructs (loading fixed at 1.000)					
Q12 → Role	1.000	1.000	0.000	n/a	n/a
Q13 → Years of Experience	1.000	1.000	0.000	n/a	n/a
Q14 → InteractionFrequency	1.000	1.000	0.000	n/a	n/a
Q15 → FlightsPerShift	1.000	1.000	0.000	n/a	n/a
Q16 → Level of Responsibility	1.000	1.000	0.000	n/a	n/a
Q17 → Operational Area / Terminal	1.000	1.000	0.000	n/a	n/a
Q18 → Passenger Type	1.000	1.000	0.000	n/a	n/a
Moderation Product Terms (loading fixed at 1.000)					
FpS × IWP → FpS × IWP	1.000	1.000	0.000	n/a	n/a
IntFreq × PPC → IntFreq × PPC	1.000	1.000	0.000	n/a	n/a
LvlResp × EMP → LvlResp × EMP	1.000	1.000	0.000	n/a	n/a
LvlResp × PPC → LvlResp × PPC	1.000	1.000	0.000	n/a	n/a
OpArea × EMP → OpArea × EMP	1.000	1.000	0.000	n/a	n/a
PassType × FSP → PassType × FSP	1.000	1.000	0.000	n/a	n/a
Role × PPC → Role × PPC	1.000	1.000	0.000	n/a	n/a
YrsExp × IWP → YrsExp × IWP	1.000	1.000	0.000	n/a	n/a

APPENDIX E: COMPARISON MATRIX: CONSISTENCY OF KEY FINDINGS WITH PRIOR STUDIES

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
S2-H1 FSP → PSP	0.584 (f^2=0.469)	Flow stability is the primary cognitive lever for predictability; largest single effect in the model.	Human–automation predictability theory predicts that environmental regularity enables accurate mental modelling and calibrated reliance. SA theory predicts regularity supports Level 3 projection.	Typically β = 0.20–0.40 in predictability studies	**Consistent but stronger**	Directionally consistent with predictability calibration theory but the effect size substantially exceeds typical magnitudes, suggesting flow stability at the gate is a particularly salient user-experience phenomenon.	Lee and See (2004); Endsley (1995); Wickens et al. (2015); Körber (2015)
S2-H2a AUT → PSP	0.321	Autonomy enhances predictability perceptions through proactive structuring of the work environment.	Demand-control model predicts decision latitude reduces uncertainty. WDQ identifies autonomy as enabling environmental structuring.	β = 0.15–0.30 typical	**Consistent**	Aligns with Karasek's demand-control model and Morgeson and Humphrey's work design framework. Magnitude within expected range.	Karasek (1979); Morgeson and Humphrey (2006); Parker et al. (2001)
S2-H2b AUT → ENG	0.398	Autonomy is a strong driver of engagement through the motivational resource pathway.	JD-R model identifies autonomy as a primary engagement resource.	ρ = 0.30–0.45 meta-analytic	**Consistent**	Fully consistent with JD-R predictions and meta-analytic estimates.	Bakker and Demerouti (2007);

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
			Meta-analyses confirm robust autonomy–engagement link.			Confirms autonomy operates as a motivational resource in technology-supported gate operations.	Christian, Garza and Slaughter (2011); Hackman and Oldham (1976)
S2-H3a PSP → PPC	0.392 (f^2=0.198)	Predictability strengthens usefulness beliefs by enabling clear attribution of system contribution.	TAM2 predicts result demonstrability and output quality drive perceived usefulness. IS success meta-analyses confirm system quality → usefulness link.	r = 0.40–0.60 corrected	**Consistent**	Aligns with TAM2 cognitive instrumental processes and DeLone-McLean system quality → usefulness pathway. Magnitude within meta-analytic range.	Venkatesh and Davis (2000); Petter, DeLone and McLean (2008); DeLone and McLean (2003)
S2-H4b JSR → ENG	0.563 (f^2=0.204)	Strain reduction is the strongest resource-to-engagement effect in the model.	JD-R health impairment process predicts demand reduction replenishes energy for engagement. Meta-analyses report hindrance demands negatively related to engagement.	ρ = 0.35–0.45 meta-analytic; hindrance ρ = −0.20	**Consistent but stronger**	Directionally consistent with JD-R but magnitude exceeds meta-analytic benchmarks, likely reflecting the acute salience of strain reduction in time-critical gate operations where congestion is a dominant hindrance demand.	Bakker and Demerouti (2017); Christian, Garza and Slaughter (2011); Crawford, LePine and Rich (2010)

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
S2-H5a CSR → PPC	0.397	Comparative superiority over legacy systems strengthens usefulness beliefs.	Prospect theory predicts reference-dependent evaluation. ECM predicts confirmation relative to prior expectations drives usefulness.	Performance expectancy is strongest UTAUT predictor	**Consistent**	Consistent with prospect theory's reference-dependent evaluation and Bhattacherjee's expectation-confirmation model. Confirms that comparative evaluation is a meaningful driver of usefulness beliefs.	Kahneman and Tversky (1979); Bhattacherjee (2001); Venkatesh et al. (2003)
S2-H6 PPC → ENG	0.525	Perceived contribution fuels engagement through internalised usefulness and self-efficacy.	TAM2 predicts usefulness strengthens motivational outcomes. Broaden-and-build theory predicts positive appraisals broaden engagement.	Limited direct comparisons	**Novel extension**	The PPC → ENG link is theoretically predicted but rarely tested directly in prior SEM studies. This finding provides new empirical evidence that usefulness beliefs energise motivational investment, bridging TAM2 and JD-R.	Venkatesh and Davis (2000); Fredrickson (2001); Bakker, Albrecht and Leiter (2011)
S2-H7a ENG → IWP	0.400	Engagement is a strong predictor of individual work performance.	Meta-analytic evidence shows engagement predicts task performance (ρ = 0.43) and contextual	ρ = 0.43 task; ρ = 0.40 contextual	**Consistent**	Closely matches meta-analytic estimates, confirming that the engagement–performance relationship generalises to	Christian, Garza and Slaughter (2011); Rich et al. (2010);

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
			performance (ρ = 0.40).			technology-supported gate operations.	Halbesleben and Wheeler (2008)
S2-H8a PPC → EMP	0.642 (f^2=0.297)	Perceived contribution is the largest direct determinant of productivity.	IS success meta-analyses report perceived usefulness → individual impact correlations of 0.30–0.56.	r = 0.56 corrected (Sabherwal et al., 2006)	**Consistent but stronger**	Substantially exceeds IS success benchmarks. Consistent with task-technology fit theory, which predicts the usefulness–productivity relationship is strongest when technology closely matches task requirements, as rtBRMS does in gate operations.	Petter, DeLone and McLean (2008); Sabherwal et al. (2006); Goodhue and Thompson (1995)
S2-H3c + S2-H9b PSP → SS = IWP → SS	Both 0.391	Cognitive clarity and realised performance contribute equally to system satisfaction.	DeLone-McLean predicts both system quality and net benefits drive satisfaction, but does not specify equal weighting. Wixom and Todd integrate belief-based and attitude-based evaluations.	No prior equal-weight finding	**Novel finding**	The equal weighting of predictability and performance in determining satisfaction is a novel finding not reported in prior IS success or airport-operations studies. Suggests that in operational technology contexts, both	DeLone and McLean (2003); Wixom and Todd (2005); Seddon and Kiew (1996)

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
						transparency and tangible outcomes matter equally.	
Indirect transmission via PPC	16 sig. paths VAF 0.21–0.87	PPC is the most active intervening construct in the structural cascade, channelling the largest number of significant indirect effects from antecedents to outcomes.	TAM2 positions perceived usefulness as the primary cognitive intervening construct between system characteristics and behavioural outcomes; DeLone–McLean positions perceived net benefits as the central intervening construct between system quality and downstream evaluation.	Indirect-effect estimates from technology-supported operator-perception models are rarely reported in airport-operations research.	**Novel extension**	Provides the most comprehensive indirect-effect evidence to date for a technology-supported operator-perception model in aviation. Corroborates TAM2 and DeLone–McLean predictions through bootstrapped specific indirect effects.	Venkatesh and Davis (2000); DeLone and McLean (2003); Zhao et al. (2010)
Moderation Stability	2 of 8 sig.	The core mechanism is robust across roles, experience, workload, passenger regimes, and operational areas.	Some human-factors research emphasises context-specificity of automation effects. JD-R predicts resource effects are	Context-specificity expected	**Partially contradicts**	Diverges from human-factors research that emphasises context-specificity (Parasuraman and Riley, 1997). The broad stability suggests	Parasuraman and Riley (1997); Bakker and Demerouti (2017)

Path/Finding	This Study (β)	Key Finding	Prior Evidence	Prior Magnitude	Verdict	Interpretation	Reference(s)
			moderated by demand levels.			the user-experience–cognitive–motivational pathway is a general feature of rtBRMS-supported operations rather than a context-specific phenomenon.	
Serial chain FSP→...→SS	β = 0.010 p = 0.031	The complete five-segment chain from flow stability to satisfaction is statistically significant.	No prior study has estimated a complete antecedent-to-satisfaction multi-segment indirect-effect chain in airport operations or IS success research.	No prior benchmark	**Novel finding**	Demonstrates that the entire theorised mechanism operates as a connected causal sequence. No comparable finding exists in the airport-operations or IS success literatures.	Hair et al. (2022); Nitzl et al. (2016); Zhao et al. (2010)

Verdict key: Consistent = finding aligns with prior evidence in both direction and magnitude. Consistent but stronger = same direction as prior evidence but effect size exceeds established benchmarks. Novel extension = finding extends prior theory into a new domain or provides first empirical test of a theoretically predicted relationship. Partially contradicts = finding diverges from some prior expectations, requiring theoretical explanation.

Note: This table should be placed in the Discussion chapter (Section 6.2/6.3) to accompany the narrative comparison with prior studies. β values are standardised path coefficients from the PLS-SEM structural model (5,000 bootstrap subsamples). Prior magnitudes are drawn from meta-analyses and benchmark studies cited in the reference column. The comparison covers both Study 1 (operational) and Study 2 (user-experience) findings.

Appendix E systematically compares each significant Study 2 structural path, indirect-effect estimate, and moderation result with the closest available prior evidence drawn from meta-analyses, foundational theoretical models, and benchmark empirical studies. For every entry, the table

reports: (a) the standardised path coefficient β obtained in this study from the PLS-SEM model with 5,000 bootstrap subsamples; (b) the substantive interpretation of the finding; (c) the relevant theoretical prediction (TAM2, JD-R, demand-control, prospect theory, IS success model, situation awareness theory); (d) the typical magnitude reported in prior literature; (e) a verdict, namely Consistent, Consistent but stronger, Novel extension, or Partially contradicts; (f) a concise interpretation locating the finding within the relevant theoretical lineage; and (g) the supporting references. The matrix covers cognitive antecedents (FSP, AUT), user-experience intervening constructs (PSP, PPC), motivational outcomes (ENG), behavioural outcomes (IWP, EMP), and attitudinal outcomes (SS), as well as the indirect-effect profile (sixteen significant indirect paths), the moderation profile (two of eight tests significant), and the complete antecedent-to-satisfaction multi-segment chain. Verdicts are assigned conservatively: a finding is labelled Consistent only when both the direction and the magnitude fall within the range reported by recent meta-analyses or canonical benchmark studies. The matrix is intended as a transparency device that allows readers to evaluate, path by path, the degree to which the present results corroborate, extend, or challenge the established literature.

APPENDIX F: GATEKEEPER INVITATION LETTER

Subject: Invitation to Participate in rtBRMS Perception Survey

Dear Colleague,

You are invited to take part in an anonymous survey about the Reat-time Boarding Route Management System (rtBRMS). The purpose of this study is to understand how security personnel, gate managers, and ground staff perceive the system in terms of efficiency, ease of use, reliability, and overall impact on gate operations.

Participation is entirely voluntary and your responses will remain completely anonymous. No personal data or identifiers (such as names, email addresses, or IP addresses) will be collected. Please do not include any personal information in your responses.

The survey should take approximately 10 minutes to complete. You may stop at any time without providing a reason, and there are no consequences for choosing not to participate.

Please find attached the Participant Information Sheet, which provides full details about the study, your rights as a participant, data protection under UK GDPR, and how your information will be handled. Please read this document carefully before deciding whether to take part.

If you agree to participate, ticking the consent checkbox at the start of the survey will confirm your voluntary agreement.

Survey Link

https://app.onlinesurveys.jisc.ac.uk/s/ucw/boarding-route-management-system-brms-study-2-perception-survey

The survey will remain open until two weeks from distribution.

Thank you very much for considering taking part in this research. Your views are valuable and will help us evaluate how BRMS can improve future gate operations.

Kind regards,

Dr. Mehran Pirhandeh

Airport Security Manager and Chair of the Research Committee Mashhad International Airport

Attachment: Participant Information Sheet (PIS)

APPENDIX G: PARTICIPANT INFORMATION SHEET

PARTICIPANT INFORMATION SHEET

TITLE OF PROJECT: EMPIRICAL ASSESSMENT OF OPERATIONAL EFFICIENCY GAINS THROUGH RULE-BASED ACCESS MANAGEMENT SYSTEM (RBAMS) IN INTERNATIONAL AIRPORTS

Invitation

The University of Worcester engages in a wide range of research which seeks to provide greater understanding of the world around us, to contribute to improved human health and well-being and to provide answers to social, economic and environmental problems.

I would like to invite you to take part in a research project which involves completing an anonymous online survey. Before you decide whether to take part, it is important that you understand why the research is being done, what it will involve for you, what information I will ask from you, and what I will do with that information. Please take time to read the following information carefully. Thank you for reading.

We will in the course of this project be collecting personal information. The UK continues to be bound by the provisions of the General Data Protection Regulation which is now the 'UK GDPR'. Under UK GDPR we are required to provide a justification (what is called a "legal basis") in order to collect such information. The legal basis for this project is "task carried out in the public interest".

You can find out more about our approach to dealing with your personal information at:
https://www.worcester.ac.uk/informationassurance/visitor-privacy-notice.html

Please take time to read this document carefully.

What is the purpose of the research?

This study aims to evaluate the perceptions of the Boarding Route Management System (BRMS), a digital gate management system that automates door operations and integrates self-service boarding. While process data (Study 1) demonstrates efficiency gains, this survey explores how airport staff perceive BRMS in terms of ease of use, usefulness, predictability, organizational readiness, and its effect on workload. The findings will contribute to understanding both operational and human dimensions of technology adoption.

Who is undertaking the research?

Name Luca Moheb
Position Doctoral Researcher (DBA Candidate), University of Worcester
Role on the project: Project Manager, Principal investigator, responsible for the design, data collection, and analysis

Who is funding the research?

This study is self-funded as part of a doctoral research project.

Why have I been invited to take part?

You have been invited because you are a security officer, gate manager, or ground staff member directly involved in gate operations. This group was selected because of its hands-on experience with BRMS and traditional gate systems. We hope to recruit approximately 150–200 participants for this study.

What will happen if I agree to take part?

If you agree, you will be asked to complete an anonymous online survey.

- The survey will be accessed via a secure link provided by the researcher or through your organization's internal communication channels.

- The survey will ask for your perceptions of BRMS, including its ease of use, usefulness, predictability, impact on workload, and organizational readiness.

- No personal data will be collected, and all questions are optional.

- The survey will take approximately 10 minutes to complete.

Do I have to take part?

No. Participation is entirely voluntary. If you decide not to take part, it will not affect your employment, training, or relationship with your organization in any way.

At the start of the survey, you will be asked to confirm that:

- You are over 18 years old

- You have read and understood the information provided

- You voluntarily agree to take part in the survey

By submitting the survey, you are providing consent for your responses to be used in the study.

You can withdraw from the study by closing your browser before submission. Once responses are submitted, withdrawal is not possible because the survey is anonymous and cannot be traced back to you.

What are the benefits for me in taking part?

Although there are no direct personal benefits, your participation will help researchers and airports better understand how BRMS is perceived by frontline staff. Findings may support future improvements in gate operations, staff training, and system design.

Are there any risks for me if I take part?

The survey has no risk. Some questions may cause you to reflect critically on work processes, but all questions are optional. If you feel uncomfortable at any point, you may skip a question or exit the survey without submitting your responses.

What will you do with my data?

- Your responses will remain completely anonymous.
- No personal or identifying information will be collected.
- Data will be stored securely on dormakaba password-protected systems.
- Results will be summarized in the doctoral thesis, presented at conferences, and may be published in academic journals. Only anonymized aggregated data will be shared.

How long will you keep my data for?
All anonymized data will be stored securely for 5 years in line with the University of Worcester's Policy for the Effective Management of Research Data. After this period, the data will be securely destroyed.

Thank you for taking the time to read this information

If you have any questions or would like further information, please contact:
Researcher: Luca Moheb – mohl1_23@uni.worc.ac.uk
DoS: Dr. Sajad Rezaei – s.rezaei@worc.ac.uk
Supervisor: Dr. Joy Garfield – j.garfield@worc.ac.uk

The University is registered with the Information Commissioner's Office. For more on the University approach to Information Assurance and Security visit: https://informationassurance.wp.worc.ac.uk/.

Allegations of Research Misconduct

To view University of Worcester's Procedures for Dealing with Allegations of Research Misconduct please click here. For information about who to contact please click here.

If you would like to speak to an independent person who is not a member of the research team, please contact the University of Worcester, using the following details:

Michelle Jellis
Secretary to Health & Sciences and Education, Culture & Society Research Ethics Panels
University of Worcester
Henwick Grove
Worcester
WR2 6AJ
ethics@worc.ac.uk

APPENDIX H: BILINGUAL SURVEY INSTRUMENT (ENGLISH–FARSI)

Note: The Farsi translation presented below is the validated version produced through the forward-backward translation procedure described in Section 4.3.6. The English original appears in the left column; the Farsi translation appears in the right column (right-to-left). The term "rtBRMS" is retained in its English abbreviation in both versions as it represents a proper system name familiar to all respondents.

Survey Title and Invitation

English	فارسی (Farsi)
Real-time Boarding Route Management System (rtBRMS) Study 2: Perception Survey	**سامانه مدیریت بلادرنگ مسیر سوارشدن rtBRMS مطالعه ۲: پرسشنامه ادراکی**
Invitation We would like to invite you to take part in a research project which involves completing an anonymous online survey. Before you decide whether to take part, it is important that you understand why the research is being done, what it will involve for you, what information I will ask from you, and what I will do with that information. Please take time to read the following information carefully. Thank you for reading.	**دعوت‌نامه** از شما دعوت می‌شود تا در یک پروژه پژوهشی شرکت کنید که شامل تکمیل یک پرسشنامه آنلاین ناشناس است. پیش از تصمیم‌گیری درباره مشارکت، مهم است که بدانید چرا این پژوهش انجام می‌شود، مشارکت شما شامل چه مواردی خواهد بود، چه اطلاعاتی از شما درخواست می‌شود و با آن اطلاعات چه خواهد شد. لطفاً اطلاعات زیر را با دقت مطالعه فرمایید. از وقتی که اختصاص می‌دهید سپاسگزاریم.

Participant Information

English	فارسی (Farsi)
What is the purpose of the research? This study aims to evaluate the perceptions of the Real-time Boarding Route Management System (rtBRMS), a digital gate management system that automates door operations and integrates self-service boarding. While process data (Study 1)	**هدف پژوهش چیست؟** هدف این مطالعه ارزیابی ادراکات کارکنان از سامانه rtBRMS (مدیریت بلادرنگ مسیر سوارشدن) است؛ یک سامانه دیجیتال مدیریت گیت که عملیات درب‌ها را خودکارسازی کرده و سوارشدن سلف‌سرویس را یکپارچه می‌کند. در حالی که داده‌های فرآیندی (مطالعه ۱) بهبود کارایی را نشان می‌دهد، این پرسشنامه

demonstrates efficiency gains, this survey (Study 2) explores how security personnel and gate managers perceive rtBRMS in terms of ease of use, usefulness, predictability, organizational readiness, and its effect on workload. The findings will contribute to understanding both operational and human dimensions of technology adoption.	(مطالعه ۲) بررسی می‌کند که پرسنل امنیتی و مدیران را از نظر سهولت استفاده، rtBRMSگیت چگونه سودمندی، اعتماد، آمادگی سازمانی و تأثیر آن بر حجم کار ارزیابی می‌کنند. یافته‌ها به درک ابعاد عملیاتی و انسانی پذیرش فناوری کمک خواهد کرد.
Who is undertaking the research? Principal Investigator: Luca Moheb, Doctoral Researcher (DBA Candidate), University of Worcester DoS: Dr Sajad Rezaei, Associate Professor, University of Worcester Supervisor: Dr Joy Garfield, Associate Professor, University of Worcester	**پژوهش توسط چه کسی انجام می‌شود؟** پژوهشگر اصلی: لوکا محب، پژوهشگر دکتری)، دانشگاه ووستر DBA(کاندیدای استاد راهنمای اول: دکتر سجاد رضایی، دانشیار، دانشگاه ووستر استاد راهنما: دکتر جوی گارفیلد، دانشیار، دانشگاه ووستر
Who is funding the research? This study is self-funded as part of a doctoral research project.	**هزینه پژوهش توسط چه کسی تأمین می‌شود؟** این مطالعه به صورت خودتأمین و به عنوان بخشی از پروژه پژوهشی دکتری انجام می‌شود.
Why have I been invited to take part? You have been invited because you are a security officer, gate manager, or ground staff member directly involved in gate operations. This group was selected because of its hands-on experience with rtBRMS and traditional gate systems. We hope to recruit approximately 150–200 participants for this study.	**چرا من برای مشارکت دعوت شده‌ام؟** شما دعوت شده‌اید زیرا افسر امنیتی، مدیر گیت یا عضو کادر زمینی هستید که مستقیماً در عملیات گیت مشارکت دارید. این گروه به دلیل تجربه عملی با rtBRMS و سامانه‌های سنتی گیت انتخاب شده است. ما امیدواریم حدود ۱۵۰ تا ۲۰۰ شرکت‌کننده برای این مطالعه جذب کنیم.
What will happen if I agree to take part? If you agree, you will be asked to complete an anonymous online survey. - The survey will be accessed via a secure link. - The survey will ask for your perceptions of rtBRMS, including its ease of use, usefulness, predictability, impact on workload, and organizational readiness.	**در صورت موافقت با مشارکت چه اتفاقی می‌افتد؟** در صورت موافقت، از شما خواسته می‌شود یک پرسشنامه آنلاین ناشناس را تکمیل کنید. - پرسشنامه از طریق یک لینک امن قابل دسترسی است. - پرسشنامه rtBRMS، را می‌پرسد، ادراکات شما از از جمله سهولت استفاده، سودمندی، قابلیت اعتماد، تأثیر بر حجم کار و آمادگی سازمانی. - هیچ اطلاعات شخصی جمع‌آوری نمی‌شود و پاسخ به

- No personal data will be collected, and all questions are optional. - The survey will take approximately 10–12 minutes to complete.	تمام سؤالات اختیاری است. - تکمیل پرسشنامه حدود ۱۰ تا ۱۲ دقیقه زمان می‌برد.
Do I have to take part? No. Participation is entirely voluntary. If you decide not to take part, it will not affect your employment, training, or relationship with your organization in any way.	**آیا مشارکت اجباری است؟** خیر. مشارکت کاملاً داوطلبانه است. اگر تصمیم به عدم مشارکت بگیرید، هیچ تأثیری بر وضعیت شغلی، آموزشی یا رابطه شما با سازمان نخواهد داشت.

Electronic Consent

English	**فارسی (Farsi)**
ELECTRONIC CONSENT: If you have viewed and understand the Participant Information Sheet please select your choice below. By clicking on the "agree" button below you indicate that you: - have read the above information; - voluntarily agree to participate; - are at least 18 years of age. If you do not wish to participate, please decline by clicking "disagree."	**رضایت‌نامه الکترونیکی:** اگر برگه اطلاعات شرکت‌کننده را مشاهده و درک کرده‌اید، لطفاً گزینه خود را در زیر انتخاب کنید. با کلیک بر دکمه «موافقم» اعلام می‌کنید که: - اطلاعات فوق را مطالعه کرده‌اید؛ - داوطلبانه با مشارکت موافقت می‌کنید؛ - حداقل ۱۸ سال سن دارید. اگر مایل به مشارکت نیستید، لطفاً با کلیک بر «مخالفم» انصراف دهید.
☐ Disagree ☐ Agree	☐ مخالفم ☐ موافقم

Section 2: Comparative Evaluation of rtBRMS (CSR1–CSR4)

Item	**English**	**فارسی (Farsi)**
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم	2 = Disagree / مخالفم	3 = Neutral / بی‌نظر	4 = Agree / موافقم	5 = Strongly Agree / کاملاً موافقم		

Q1 (CSR1)	Compared to the traditional system, rtBRMS makes gate and door transitions easier to manage.	مدیریت تغییر rtBRMSدر مقایسه با سامانه سنتی، وضعیت گیت‌ها و درب‌ها را آسان‌تر می‌کند.
Q2 (CSR2)	rtBRMS reduces the time required to prepare and execute boarding or deboarding.	زمان لازم برای آماده‌سازی و اجرای rtBRMS سوارشدن یا پیاده‌شدن مسافران را کاهش می‌دهد.
Q3 (CSR3)	Coordination between gate staff, security, and ground handlers runs more smoothly when rtBRMS is used.	هماهنگی بین کارکنان گیت، امنیت و عوامل زمینی روان‌تر انجام می‌شود.rtBRMSهنگام استفاده از
Q4 (CSR4)	Overall operational handling performance is improved with rtBRMS compared to the traditional system.	در مقایسه rtBRMSعملکرد کلی عملیات هندلینگ با با سامانه سنتی بهبود یافته است.

Section 3: Flow Stability Perception – FSP (Q5–Q8)

Item	**English**	**فارسی (Farsi)**
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم | 2 = Disagree / مخالفم | 3 = Neutral / بی‌نظر | 4 = Agree / موافقم | 5 = Strongly Agree / کاملاً موافقم		
Q5 (FSP1)	Passenger movement feels more stable and less erratic when rtBRMS is active.	پایدارتر و rtBRMSحرکت مسافران هنگام فعال بودن کمتر نامنظم احساس می‌شود.
Q6 (FSP2)	With rtBRMS, sudden surges or drops in flow are less common.	، افزایش یا کاهش ناگهانی جریان مسافران rtBRMSبا کمتر رخ می‌دهد.

Q7 (FSP3)	The boarding and deboarding process feels smoother when rtBRMS is used.	فرآیند سوارشدن و پیاده‌شدن هنگام استفاده از rtBRMS روان‌تر احساس می‌شود.
Q8 (FSP4)	rtBRMS helps maintain a steady pace of passenger movement.	rtBRMS به حفظ سرعت یکنواخت حرکت مسافران کمک می‌کند.

Section 4: Perceived System Predictability – PSP (Q9–Q12)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم 2 | Disagree / مخالفم 3 | Neutral / بی‌نظر 4 | Agree / موافقم 5 | Strongly Agree / کاملاً موافقم		
Q9 (PSP1)	rtBRMS behaves consistently across comparable gate conditions.	در شرایط مشابه گیت، رفتار یکسانی از خود rtBRMS نشان می‌دهد.
Q10 (PSP2)	I can anticipate how rtBRMS will act when passenger flows change.	هنگام تغییر جریان مسافران می‌توانم پیش‌بینی کنم که rtBRMS چگونه عمل خواهد کرد.
Q11 (PSP3)	The decisions taken by rtBRMS during boarding or deboarding are predictable.	در حین سوارشدن یا پیاده‌شدن تصمیماتی که rtBRMS اتخاذ می‌کند، قابل پیش‌بینی هستند.
Q12 (PSP4)	The routing and pacing actions of rtBRMS are easy to foresee in real time.	به‌صورت بلادرنگ به‌راحتی قابل پیش‌بینی هستند. rtBRMS اقدامات مسیریابی و تنظیم سرعت

Section 5: Perceived Autonomy – AUT (Q13–Q15)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم | 2 = Disagree / مخالفم | 3 = Neutral / بی‌نظر | 4 = Agree / موافقم | 5 = Strongly Agree / کاملاً موافقم		
Q13 (AUT1)	rtBRMS allows me to manage gate timing and sequencing with more control.	به من امکان می‌دهد زمان‌بندی و ترتیب عملیات rtBRMS گیت را با کنترل بیشتری مدیریت کنم.
Q14 (AUT2)	I feel able to intervene proactively when unexpected events occur.	احساس می‌کنم می‌توانم هنگام وقوع رویدادهای غیرمنتظره به‌صورت پیشگیرانه مداخله کنم.
Q15 (AUT3)	Flow stability from rtBRMS gives me greater operational autonomy.	استقلال عملیاتی بیشتری rtBRMSپایداری جریان ناشی از به من می‌دهد.

Section 6: Job Stress Reduction – JSR (Q16–Q18)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم | 2 = Disagree / مخالفم | 3 = Neutral / بی‌نظر | 4 = Agree / موافقم | 5 = Strongly Agree / کاملاً موافقم		
Q16 (JSR1)	Peak-time boarding and deboarding feel less stressful with rtBRMS.	rtBRMSسوارشدن و پیاده‌شدن در ساعات اوج با کم‌استرس‌تر احساس می‌شود.
Q17 (JSR2)	I experience less time pressure at the gate when passenger flows	تثبیت می‌شود، rtBRMSهنگامی که جریان مسافران توسط فشار زمانی کمتری در گیت تجربه می‌کنم.

	are stabilised by rtBRMS.	
Q18 (JSR3)	rtBRMS reduces my concerns about congestion near doors or aisles.	نگرانی‌های من درباره ازدحام در نزدیکی درب‌ها rtBRMS یا راهروها را کاهش می‌دهد.

Section 7: Work Engagement – ENG (Q19–Q21)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم	2 = Disagree / مخالفم	3 = Neutral / بی‌نظر	4 = Agree / موافقم	5 = Strongly Agree / کاملاً موافقم		
Q19 (ENG1)	I feel energised when carrying out my tasks while rtBRMS is in use.	احساس انرژی rtBRMSهنگام انجام وظایفم در زمان استفاده از و نشاط می‌کنم.
Q20 (ENG2)	I am enthusiastic about performing gate-related tasks supported by rtBRMS.	rtBRMSنسبت به انجام وظایف مرتبط با گیت که توسط پشتیبانی می‌شوند، اشتیاق دارم.
Q21 (ENG3)	I become absorbed in my work during gate operations when rtBRMS is active.	، در کارم غرق rtBRMSهنگام عملیات گیت و فعال بودن می‌شوم.

Section 8: Perceived Performance Contribution – PPC (Q22–Q24)

Item	English	فارسی (Farsi)

Response Scale: 1 = Strongly Disagree / کاملاً مخالفم = 2 | Disagree / مخالفم = 3 | Neutral / بی‌نظر = 4 | Agree / موافقم = 5 | Strongly Agree / کاملاً موافقم		
Q22 (PPC1)	rtBRMS helps me perform my gate tasks more effectively.	به من کمک می‌کند وظایف گیت خود را مؤثرتر انجام دهم. rtBRMS
Q23 (PPC2)	rtBRMS contributes to the quality of my work.	به کیفیت کار من کمک می‌کند. rtBRMS
Q24 (PPC3)	rtBRMS supports me in working more efficiently during turnarounds.	از من در کار کردن کارآمدتر در طول عملیات بازگشت rtBRMS پشتیبانی می‌کند.

Section 9: Individual Work Performance – IWP (Q25–Q27)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم = 2 | Disagree / مخالفم = 3 | Neutral / بی‌نظر = 4 | Agree / موافقم = 5 | Strongly Agree / کاملاً موافقم		
Q25 (IWP1)	I complete my gate tasks accurately and with attention to detail.	وظایف گیت خود را با دقت و توجه به جزئیات انجام می‌دهم.
Q26 (IWP2)	I achieve the expected performance level in gate operations.	به سطح عملکرد مورد انتظار در عملیات گیت دست می‌یابم.

Q27 (IWP3)	I handle my workload effectively, even during demanding gate situations.	حجم کار خود را به‌طور مؤثر مدیریت می‌کنم، حتی در شرایط پرفشار گیت.

Section 10: Employee Productivity – EMP (Q28–Q30)

Item	English	فارسی (Farsi)
Response Scale: 1 = Strongly Disagree / کاملاً مخالفم | 2 = Disagree / مخالفم | 3 = Neutral / بی‌نظر | 4 = Agree / موافقم | 5 = Strongly Agree / کاملاً موافقم		
Q28 (EMP1)	With rtBRMS, I can handle more tasks within the same time frame.	می‌توانم وظایف بیشتری را در همان بازه زمانی انجام rtBRMSبا دهم.
Q29 (EMP2)	rtBRMS enables higher productivity during gate turnarounds.	بهره‌وری بالاتری را در طول عملیات بازگشت گیت rtBRMS ممکن می‌سازد.
Q30 (EMP3)	The use of rtBRMS improves overall efficiency in gate operations.	کارایی کلی عملیات گیت را بهبود می‌بخشد.rtBRMSاستفاده از

Section 11: System Satisfaction – SS (Q32–Q34)

Item	English	فارسی (Farsi)

Response Scale (7-point): 1 = Strongly Disagree / کاملاً مخالفم = 2 / Disagree / مخالفم = 3 / Slightly Disagree / تا حدی مخالفم = 4 / Neutral / بی‌نظر = 5 / Slightly Agree / تا حدی موافقم = 6 / Agree / موافقم = 7 / Strongly Agree / کاملاً موافقم		
Q32 (SS1)	Overall, I am satisfied with rtBRMS as a support system for gate operations.	به عنوان یک سامانه پشتیبان عملیات گیت rtBRMSبه‌طور کلی، از رضایت دارم.
Q33 (SS2)	rtBRMS meets my expectations as a tool for managing passenger flow.	انتظارات من را به عنوان ابزاری برای مدیریت جریان rtBRMS مسافران برآورده می‌کند.
Q34 (SS3)	I would prefer to use rtBRMS rather than operate without it.	استفاده کنم تا اینکه بدون آن کار کنم.rtBRMSترجیح می‌دهم از

Section 12–18: Demographic and Contextual Variables

Item	**English**	**فارسی (Farsi)**
Q12: Role at Airport / نقش شما در فرودگاه		
	☐ Safety Personnel ☐ Security Personnel ☐ Gate Agent ☐ Gate Manager ☐ Dispatcher ☐ Ground Handling ☐ Supervisor ☐ Other (please specify)	☐ پرسنل ایمنی ☐ پرسنل امنیتی ☐ مأمور گیت ☐ مدیر گیت ☐ دیسپچر ☐ خدمات زمینی ☐ سرپرست ☐ سایر (لطفاً مشخص کنید)
Q13: Years of Experience in Gate Operations / سابقه کار در عملیات گیت		

	☐ Less than 1 year ☐ 1–3 years ☐ 4–7 years ☐ 8–15 years ☐ More than 15 years	☐ کمتر از ۱ سال ☐ ۱ تا ۳ سال ☐ ۴ تا ۷ سال ☐ ۸ تا ۱۵ سال ☐ بیش از ۱۵ سال
Q14: Frequency of Interaction with rtBRMS / میزان تعامل با rtBRMS		
	☐ Daily ☐ Several times per week ☐ Occasionally ☐ Rarely	☐ روزانه ☐ چند بار در هفته ☐ گاهی اوقات ☐ به‌ندرت
Q15: Flights Typically Handled per Shift / تعداد پروازهای معمول در هر شیفت		
	☐ 1–3 ☐ 4–6 ☐ 7–10 ☐ More than 10	☐ ۱ تا ۳ ☐ ۴ تا ۶ ☐ ۷ تا ۱۰ ☐ بیش از ۱۰
Q16: Primary Level of Responsibility for rtBRMS / سطح اصلی مسئولیت شما در قبال rtBRMS		
	☐ Direct operation (actively controlling gates) ☐ Monitoring and supervision ☐ Passenger assistance ☐ Troubleshooting / technical support ☐ Management oversight	☐ عملیات مستقیم (کنترل فعال گیت‌ها) ☐ نظارت و سرپرستی ☐ کمک به مسافران ☐ عیب‌یابی / پشتیبانی فنی ☐ نظارت مدیریتی
Q17: Primary Operational Area / حوزه عملیاتی اصلی		

	☐ Terminal A (Domestic) ☐ Terminal B (International) ☐ Remote stands ☐ Mixed areas	☐ ترمینال الف (داخلی) ☐ ترمینال ب (بین‌المللی) ☐ پارکینگ‌های دور (ریموت استند) ☐ مناطق ترکیبی
Q18: Primary Passenger Type / نوع اصلی مسافران		
	☐ Mainly departures ☐ Mainly arrivals ☐ Both equally	☐ عمدتاً خروجی ☐ عمدتاً ورودی ☐ هر دو به‌طور مساوی

End of Appendix H. This bilingual instrument was produced through the forward-backward translation procedure described in Section 4.3.8, validated through expert panel review, cognitive interviews with five bilingual operational staff, and pilot testing with approximately 30 respondents (all constructs $\alpha \geq 0.70$).