UNIVERSITY of WORCESTER

ENHANCING THE STUDENT JOURNEY: A QUALITATIVE EXPLORATION OF CONVERSATIONAL AGENTS IN HIGHER EDUCATION MARKETING

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DECLARATION

I 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.

Signed:

Date: 27th June 2024

ABSTRACT

Conversational agents are profoundly changing the marketing landscape and the marketing communications strategies of higher education institutions (HEIs) in the UK. Another channel has been added to the marketing communications mix of HEIs: prospective students can now communicate with potential universities through the medium of chatbots on websites. HEIs are adapting their student recruitment activities by utilising the new channel to capture the attention of prospective students at the information searching stage of their student journey. This study adopted the social constructionism paradigm. It evaluated the effectiveness of conversational agents at the start of the student journey and investigated the factors leading to successful human–machine interactions, which can improve student experiences. In addition to reviewing the literature on the impact of conversational agents on marketing communications, qualitative data were collected from 24 participants divided into three groups– undergraduate students, postgraduate students and marketing professionals – interacting with conversational agents during task-based, semi-structured interviews. Thematic analysis of the data revealed four themes: user experience and interaction, functionality and usability, trust and privacy, and emotional and perceptual aspects. The themes form the core of a conceptual framework that offers practical insights into the design and launch of chatbots used for student recruitment. Theoretical contributions of the research develop understanding and application of the elaboration likelihood model and the unified theory of acceptance and use of technology 2 in the context of current artificial intelligence technologies. Recommendations are presented for HEIs embarking on the path of deploying conversational agents in their marketing communications strategies.

KEYWORDS: Artificial intelligence, conversational agents, marketing communications, student journey, chatbots, user experience, functionality, trust, emotions, perceptions

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LIST OF ABBREVIATIONS

AI	artificial intelligence
AIDA	Attention, Interest, Desire, Action
AR	augmented reality
B2B	business-to-business
B2C	business-to-consumer
CA	conversational agent
CRM	customer relationship management
ELM	elaboration likelihood model
EU	European Union
GDPR	General Data Protection Regulation
GP	general purpose
GPT	Generative Pre-Trained Transformer
HE	higher education
HEI	higher education institution
HRI	human–robot interaction
HRM	human resource management
IMC	integrated marketing communications
IT	information technology
LLM	large language model
ML	machine learning
NLP	natural language processing
PG	postgraduate
RPA	robotic process automation
SB	speech-based
SD	specific domain
TB	text-based
TAM	technology acceptance model
UG	undergraduate
UTAUT	unified theory of acceptance and use of technology
VR	virtual reality

CHAPTER ONE
INTRODUCTION

1.1 Introduction and Background of the Study

Artificial Intelligence (AI) has become increasingly prevalent in many industries, including education. One area in which AI is being utilised is student recruitment. AI is being used to streamline the recruitment process, reduce costs, and improve the quality of applicants. One way is through the use of chatbots. Chatbots are computer programs that can simulate conversation with human users. They can be used to answer common questions, provide information about programs and services, and even help students apply to programs. For example, Georgia State University has implemented a chatbot named Pounce that answers student questions about the application process and provides personalized guidance (Biwer, 2021).

The previous paragraph was written by Chat Generative Pre-Trained Transformer (GPT), which is the first large language model (LLM) made available to the mass public for free use; ChatGPT was launched in November 2022 (Open.ai, 2022). LLMs are one of the technologies that power modern conversational agents (CAs), also known as chatbots (van Dis et al., 2023). LLMs are machine-based algorithms that have been trained on large amounts of data and can generate coherent and sophisticated text which, in most cases, is indistinguishable from human-generated writing. In just a few months, ChatGPT has disrupted many industries, academia and professions. For example, positive customer interactions are a key factor in the success of e-commerce organisations; however, these services can be costly and time-consuming. Therefore, LLMs are often deployed to automate some of the processes without the need to invest in and train new human resources, which thus reduces cost and increases speed and accuracy (George and George, 2023). In healthcare, ChatGPT can be deployed at the beginning of a patient's medical treatment when collecting personal and medical information about their condition; in addition, ChatGPT can be used at the end of the treatment to write the discharge summary, for example, at the end of a hospital stay (Patel and Lam, 2023).

The world of academia has been profoundly transformed by the capabilities of ChatGPT and its impact on the ethics and integrity of academic research. In one study, ChatGPT was tasked to generate a literature review on the topic of "Digital Twins in Healthcare" (Aydin and Karaarslan, 2022). In another study, Khalil and Er (2023) demonstrated the originality of ChatGPT-generated text by testing it through plagiarism software; they concluded that the text was highly original and that the chance of detecting that the text was not produced by a human being was very low.

These examples demonstrate the current capabilities of intelligent CAs, which are one of the emerging technologies disrupting marketing communications. Other technologies, such as the Internet of Things, big data, blockchain, augmented reality (AR), virtual reality (VR) and mixed reality, are also fundamentally influencing the way organisations interact with their prospective and existing customers (Coronado, Itadera and Ramirez-Alpizar, 2023; Hoyer et al., 2020; Anshari et al., 2018; Bolton et al., 2018). However, compared to other emerging technologies, AI is believed to have had the most profound impact on the marketing mix and strategy of organisations across many industries and geographical locations (Ungerman and Dědková, 2019; Eriksson, Bibi and Bonera, 2020; Nanayakkara, 2020; Verma et al., 2020; Huang and Rust, 2022; Mehta et al., 2022). Huang and Rust (2022) went one step further and proposed a new “Collaborative Artificial Intelligence Framework” in marketing that specifies the steps necessary for a successful interface between marketers and AI; the framework aimed to help organisations capitalise on the respective strengths and weaknesses of AI and human intelligence.

Daugherty and Wilson (2018) also conceptualised a collaborative framework for an interface between humans and AI in what they call the “missing middle”. The new generation of AI-powered tools are trained to react to, and learn from, changes in their environment, and to comprehend, learn and act all thanks to the advances in machine learning (ML). These capabilities could make humans fear the possibility of machines replacing them in the world of work; however, Daugherty and Wilson (2018) proposed that we should not see AI as a potential threat and the enemy, but as a tool to amplify our skills. Collaboration between AI-powered tools and humans could achieve productivity gains never seen before. This collaborative space is called the “missing middle”, because very few organisations are operating in this space where humans complement the tasks performed by machines and machines give humans “superpowers”, such as the analysis of enormous amounts of data in real time (Daugherty and Wilson, 2018).

The use of AI in current marketing practices has spread to many tasks and functions; it provides insights, automation, and aids decision-making processes (Huang and Rust, 2020, 2022). Some applications of AI tools are invisible to the customer, such as predictive analytics and content creation; others are at the forefront of the customer interaction aspects of marketing, such as personalisation and customer service. All these four applications (predictive analytics, content creation, personalisation and customer service) are interconnected and interdependent. Predictive analytics is concerned with gathering and analysing large amounts of real-time customer data with the purpose of generating insights, trends and recommendations that meet customers' evolving requirements (Wirth, 2018; Surendro, 2019; McCarthy et al., 2022). ChatGPT and other similar LLMs sit behind the innovations that are observed in the space of content creation; in this space, marketers have at their fingertips a fast and effective tool that generates user content with high precision and originality. The content generated can surpass some of the content generated by new graduates who have joined a marketing team straight from university (Vlačić et al., 2021; Lund and Wang, 2023, Rashkova et al., 2023). AI tools are designed to provide insights into consumer behaviours, attitudes, actions and expectations; algorithms are trained to predict a customer's next move and create a unique and personalised customer experience (Kumar et al., 2019; Tong, Luo and Xu, 2020; Thomaz et al., 2020). AI tools such as chatbots are also increasingly supporting customer service departments by either completely replacing the human agents and answering customer enquiries, such as providing product information and resolving complaints quickly, or by providing insights and support to the human agent by highlighting relevant information about the customer or previous interactions (Huang and Rust, 2018; Ling et al., 2021; Wang, Lin and Shao, 2022).

AI is an umbrella term encompassing an array of technologies, such as computer vision, goal-driven systems, pattern recognition, autonomous systems and natural language processing (NLP; Russell and Norvig, 2022). When these technologies are classified through the lens of business priorities for marketing communication, they can be grouped into three broad categories: process automation, generating insights and customer engagement (Davenport and Ronanki, 2018). The first category is automation of both physical and digital tasks, typically the back-office administrative and financial activities, which is usually referred to in the literature as robotic process automation (RPA). RPA tools are more advanced than non-intelligent automation tools due to their ability to act like a human (Bornet, Barkin and Wirtz, 2021; Flechsig, Anslinger and Lasch, 2021). In the field of marketing, RPA is deployed when there is a need for auto-negotiation, recommendation, customer relationship management (CRM) or content creation (Ting, Yen and Yang, 2021). The second category applies to algorithms that are fed with large volumes of data and tasked with discovering patterns, correlations and trends to generate insights. These insights allow marketers to predict what customers are likely to buy and create personalised targeted ads, and they alert the marketing team to issues in real time (Davenport and Ronanki, 2018; Strycharz et al., 2019; Zanker, Rook and Jannach, 2019). The third category, customer engagement, is the domain of CAs, chatbots and virtual assistants and the topic of this research study. CAs, chatbots and virtual assistants are powered by technologies such as natural language understanding and natural language generation, collectively known as NLP, which are from the domain of ML and deep learning (Zhang and Lu, 2021). When NLP is coupled with algorithms trained in predictive analytics, the possibilities for customer interaction and engagement exponentially expand across platforms, devices and channels across the entire customer journey (Singh et al., 2021).

The advent of these new AI tools has fundamentally altered the consumer journey from the traditional linear progression through stages, which is predominantly driven by human interaction, to a more complex and unpredictable path between stages, which is driven by interaction with machines. Models such as Attention, Interest, Desire, Action (AIDA; Wijaya, 2015) and Learn, Feel and Do (Kim, Jiang and Bruce, 2021) trace the customer journey. Virtual assistants, such as Amazon's Echo, Google's Nest Hub and Apple's HomePod, are contributing to this trend by making AI tools more accessible and less scary for the general public; these virtual assistants are packaged in the form of smartphones or smart speakers (Davenport et al., 2020; Davenport, Guha and Grewal, 2021), and, more recently, ChatGPT can be accessed on mobile phones via apps (Open.ai, 2023). The popularity of virtual assistants is estimated to grow to the staggering level of eight billion globally (Liu, 2021); this suggests a step change in the way customers will browse and shop online, find relevant product information, log complaints and post reviews for other customers to read. To remain competitive, organisations must develop and invest in omnichannel marketing strategies that include CAs if they wish to remain relevant to the evolving needs of customers. What this means in practice is that companies must effectively integrate both their offline and online channels and feed them with consistent communication throughout the customer journey: before, during and after purchase (Hoyer et al., 2020; Palazón et al., 2022). The customer journey consists of a variety of touchpoints: brand-owned, partner-owned, customer-owned and social touchpoints (Lemon and Verhoef, 2016). Touchpoints are influenced by technological developments and ultimately change the dynamics of the entire customer journey (Nam and Kannan, 2020).

Like other industries, higher education (HE) has kept up with the pace of development and widely adopted AI tools to support, augment and improve the student experience. Over the last 30 years a seismic shift has been observed in education's goals and practices and in the educational environment with the trends being accelerated by advances in, and accessibility to, technology (Roll and Wylie, 2016). Education's goals have evolved from providing students with static domain knowledge about a particular profession or industry to a more dynamic set of skills that develops students' adaptive attitudes for on-the-job learning, critical thinking, metacognition and collaboration (Chen, Chen and Lin, 2020; Cox, 2021; Chen et al., 2023). Current classroom practices are becoming much more reflective of the real-world environment that students will encounter after leaving formal education; they are exposed to more experiential learning, groupwork, gamification and personalised content (Bennani, Maalel and Ben Ghezala, 2021; Cunningham-Nelson et al., 2019; Caballé and Conesa, 2019). The educational environment is also shifting towards a lifelong learning approach where employees do not stop learning after they complete their formal education. This is reflected in the proliferation of massive open online courses, known as MOOCs, and nanodegrees, offered by HE institutions (HEIs), which are made possible by advances in technology and AI (Alam, 2021; Caballé and Conesa, 2019; Roll and Wylie, 2019).

Student recruitment, the period preceding students' time spent studying at an HEI, is also impacted by AI; the literature does not consider student recruitment to be part of the student journey. Over the past decade, HEIs have implemented fundamental changes in the way they market their brand to potential students. There are several factors that have influenced this strategic shift in marketing strategies: technological, demographic and economic. With the increase in complexity and interconnectedness afforded by internet technologies, HEIs recognise the importance of utilising not only the traditional channels of recruitment, such as student fairs and educational agent networks, but also borderless internet platforms, such as social media (Chugh and Ruhi, 2018; John, Walford and Purayidathil, 2022). These platforms are used to run marketing campaigns that aim to attract both domestic and international students (Le, Dobele and Robinson, 2019; Lomer, Papatsiba and Naidoo, 2018); they specifically target potential students from the digitally native generation using mobile-based Web 2.0 (Wong et al., 2022). Pursuing competitive market advantage and treating students more like “customers” (Dennis et al., 2016), most HEIs now have as a minimum social media accounts with Facebook, X (formerly Twitter), Instagram and YouTube, and some have an account with Snapchat. HEIs use these social media accounts for two main purposes: (1) to provide up-to-date information about their programmes, events and campuses; (2) to serve as a channel for communication between their internal and external stakeholders, such as students, parents, faculty and alumni (Cingillioglu, Gal and Prokhorov, 2023). The effectiveness of these platforms has been the focus of studies that, for example, correlate the number of tweets posted by a given university and the number of students that prefer to study there (Cingillioglu, Gal and Prokhorov, 2021) or the link between frequency of posting and reaching a more diverse audience (Prabowo, Bramulya and Yuniarty, 2020).

From an economic viewpoint, HEIs have experienced additional pressures resulting from the marketplace becoming more competitive in both the domestic and international arena. This has been caused by factors affecting both supply and demand: supply has remained largely static and unchanged whereas demand has significantly decreased because of higher costs, more options such as apprenticeships and the decoupling of the link between career prospects and level of education (Jeckells, 2022; Lomer, Papatsiba and Naidoo, 2018; Perera, Nayak and Nguyen 2022; Quach and Thaichon, 2022). Even though international HE has been growing in popularity, especially in territories such as South-East Asia and the Middle East, it has been rapidly declining in North America, Europe and Australia where the next generation of students are exploring alternative paths to starting a career or owning a business (De Wit and Altbach, 2020; Schweiger and Ladwig, 2018).

This shift in perceptions and priorities demonstrates the demographic shift in the target audience of HEIs and the gradual transitioning from educating Millennials (individuals born between the early 1980s and mid-1990s) to preparing the next generation, Generation Z (individuals born between 1996 and 2012), for the expectations of employers and the marketplace in general (Schweiger and Ladwig, 2018). Millennials use social media channels as their main mode of communication with brands and organisations (Helal, Ozuem and Lancaster, 2018). Generation Z shares this trait of the previous generation but also brings new patterns of behaviour, such as seeking a good cultural fit with the organisations they interact with as well as aiming to get good value from each interaction (Gabrielova and Buchko, 2021). Generation Z is also reported to value trust and fairness, and to be more connected, self-educated, self-sufficient and entrepreneurial than previous generations (Ernst and Young, 2016).

Taking into account the technological, economic and demographic challenges that HEIs face, as detailed above, and capitalising on the advances in AI communication technologies, which are flooding the market, HEIs are exploring chatbots as a tool to meet these challenges and help them remain competitive in a difficult and volatile market. Some HEIs are already experimenting with chatbot deployment along one or more of the dimensions identified by Cheng and Jiang (2022):

a) interaction – two-way communication with prospective students with the aim to initiate value co-creation conversations (Glyptou, 2020; Xie and Keh, 2020);
b) information – chatbots have been designed to answer questions about course registration, timetables, financial issues, academic queries and more (Brill, Munoz and Miller, 2019);
c) accessibility – chatbots make complex information accessible anywhere, any time and on any device (Cheng and Jiang, 2022);
d) entertainment – chatbots can make dry and procedural information that the students need to know about rules and regulations engaging and entertaining and thus more likely to be remembered (Gonçalves et al., 2022);
e) customisation – chatbots are programmed to remember previous interactions with students, therefore, each student’s preferences and information can be used to build an individualised profile with each subsequent conversation (Tong, Luo and Xu, 2020).

Recent trends indicate that chatbots as a technology are not only here to stay, but they will also become a critical channel for communication with customers. The explosion in generative AI tools, such as ChatGPT, Gemini (formerly known as Bard) and DALL-E, and the myriad of application programming interface tools being currently developed, pave the way for conversational AI technology to become an essential tool in marketing communications across most industries, including HE (Gursoy, Li and Song, 2023; Pandey, 2023; Ratten and Jones, 2023).

1.2 Research Problem

The underlying aim of this research study is to contribute to the evolving knowledge on the role that chatbots, and other conversational AI tools, play in the student journey. More specifically, this study focuses on the stage of the student journey that the literature terms as “student recruitment”; student recruitment is usually explored as a stage that is separate from the rest of the student journey through HE (Ortagus and Tanner, 2019). This presents two problems that need further exploration. The first problem is that from a student’s point of view, student recruitment is an essential part of their journey; it sets the scene for all future stages and decisions along the journey – from induction, through study, all the way to graduation. If this initial stage of the journey is disconnected from the remainder of the process, then a student might encounter disappointment and challenges further down the line. The link between choices made during the student recruitment stage and student satisfaction during the student journey stage has not been explored in the literature; in particular, studies have not asked whether technology and communication channels shape a student’s early decisions in their student journey. A conversational AI tool, such as a chatbot, may be a deciding factor in better matching the strengths and weaknesses of a student with their desired professional path. This study explores the role such tools play in the student recruitment stage when students evaluate their options and actively look for information and advice about the best match between their skills, aspirations and available courses.

The second problem in the context of HEIs is that the adoption of AI tools has been prevalent in the part of the student journey where students interact with learning material. The majority of studies of chatbots conducted so far are on tools deployed to aid students once they have started their courses; there are library assistants, assessment assistants, well-being assistants and language assistants (Weaver, 2013; Chen et al., 2023). Very few studies concentrate on the AI tools made available to applicants to either guide them to the correct choice of course to study or to guide them through what is usually a complex application process. The challenge HEIs are going to face in the coming years is the way prospective students will be using the information provided through generative AI tools such as ChatGPT. These tools will disrupt the student recruitment market and HEIs need to be ready to either respond to this additional threat or be left behind in the race for the next generation of students. ChatGPT has already shifted the focus of student search for, and selection of, HEI choices with its lightning quick analysis of available web data and the ability to be almost infinitely personalised (Dwivedi et al., 2023; Deng and Lin, 2022). More so, it removes the priority of current student recruitment channels to feature and favour HEIs that pay for occupying top spots on search pages. There will be no need to pay for agents and comparison sites because the students can do the searching and comparing for themselves. A student situated anywhere in the world is already able to search globally for university courses on the subjects they are interested in, in locations of their choice, at the entry grades they have achieved, the level of English language they possess and at the price they are prepared to pay.

As a result of these dual problems, the purpose of this study is to contribute to this field of knowledge, using a social constructivist perspective, by developing a conceptual framework that can be adopted by HEIs in their response to the changing expectations of Generation Z students entering HE and the adoption of ever-evolving AI tools in the communication channels with prospective students.

1.3 Research Aim and Objectives

The aim of this study is to explore the impact of incorporating CAs into the marketing communications strategies of HEIs from the point of view of improving student experiences at the start of their holistic student journey.

In support of the overall aim, the following four objectives have been identified.

Objective 1

To review existing studies relating to CAs, HE marketing communications and the student journey.

This study begins by critically evaluating the extant literature on the concepts of AI in general, conversational AI, student journey, customer journey and student recruitment. The application of conversational AI tools in other industries and across the seven Ps (product, price, place, promotion, people, process and physical evidence) of the marketing mix indicates current capabilities outside the HEI space. The social constructivist paradigm guides the researcher's ontological and epistemological orientations in considering the nature of participants' personal experiences with CAs.

Objective 2

To critically examine the effectiveness of CAs at the early stages of the student journey with a focus on users' attitudes, beliefs and intentions to interact with CAs for the purpose of information gathering.

To address this objective empirical research is conducted in the form of semi-structured, task-based interviews incorporating think-aloud protocols; participants are asked to interact with a CA for the purpose of gathering course and institution information, and then they were guided through an interview where they were asked to reflect on the experience and their attitudes in general towards interacting with the technology. The answers from the participants were analysed using thematic analysis. The emerging themes provided the foundation for determining the factors and concepts that would inform the next objective.

Objective 3

To investigate the conditions necessary to result in successful human–machine interactions with CAs, which in turn would translate into improved student experiences at the information gathering stage.

The interaction between prospective students and CAs can be examined in the global context of customer experience by exploring concepts such as usefulness, ease of use, trust, privacy, ethics, personalisation, anthropomorphism and others that shape human–machine interaction at the level of marketing communication with a potential student. The elaboration likelihood model (ELM) (Petty and Cacioppo, 1986) and the unified theory of acceptance and use of technology 2 (UTAUT2) (Venkatesh, Thong and Xu, 2012) provide the theoretical framework onto which the concepts are based.

Objective 4

To develop a conceptual framework comprising a structured decision-making process aimed at HEIs wishing to deploy CAs to enhance the student journey.

The study develops a conceptual framework that provides insight into how the identified concepts relate to the specific stage of the student journey when students select their courses and universities. It also provides a path to adopting such a framework when choosing to deploy a CA for the first time. Improvements in satisfaction with the student journey can be directly linked to the importance the individual concepts bear on the decision-making process of prospective students.

1.4 Research Questions

To address the first objective the following research question is examined:

(1) What are the research gaps in relation to the topic of the use of CAs, their use in the field of HE marketing communications and in the student journey?

The question is addressed through a critical review of the extant literature to provide a historical perspective as well as examples of wide application in other industries. A taxonomy of CAs clarifies the technological capabilities of these AI tools, and analysis of the consumer journey is linked to the concept of the student journey.

To address the second objective the following research question is examined:

(2) What attitudes, beliefs and intentions contribute to users' successful interaction with CAs in the information gathering stage of the student journey?

The question is addressed through conducting thematic analysis of the findings and comparing the results with the literature.

To address the third objective the following research question is examined:

(3) What are the conditions necessary for successful human–machine interaction with CAs that would result in an improved student experience at the information gathering stage?

The answer to this question will highlight the concepts that underpin customer relationships in general and, more specifically, in the context where one of the parties in the communication is not human. The ELM model is particularly relevant here to provide explanation for the strengths and weaknesses of CAs according to their current capabilities, while the UTAUT2 model provides a clear path of enquiry when exploring ease of use and usefulness as concepts.

To address the fourth objective the following research question is examined:

(4) Which key concepts identified through the previous two questions are most pertinent in the context of HEIs and the early stages of the student journey that result in a conceptual framework for decision making?

This final question aims to provide weighting of importance for the factors and concepts identified through the critical review of the extant literature and the results of the analysis of the empirical data. It also aims to summarise the findings in a practical and applicable conceptual framework that can be adopted by HEIs deploying CA technologies for the first time in their marketing strategies or seeking to improve student satisfaction linked with their existing marketing strategies and campaigns.

1.5 Rationale for the Study

Research interest in the topic of conversational AI and its application in various contexts has exploded in recent years, and was significantly accelerated by the launch of ChatGPT in November 2022 (Open.ai, 2023). Conversational AI tools have been adopted in many processes and departments in a variety of industries, including in the various stages of the marketing process (McTear and Ashurkina, 2024, Ozuem et al., 2024). State-of-the-art research in 2023 and 2024 pointed to an increasing focus on human-centric design, ethical considerations and generative AI tools discussed as directions for current and future research at the 4th European Chatbot and Conversational AI Summit in March 2024. Studies published more broadly in the area of marketing communications and consumer engagement tackle topics such as: the role of generative AI and anthropomorphism in shaping conversational marketing (Israfilzade, 2023); how conversational AI tools can provide a personal touch and improve customer experience in the customer service context (Blümel, Zaki and Bohné, 2024); the shift to dynamic AI-driven interactions that personalise customer experiences in marketing communications (Israfilzade and Sadili, 2024); and the role conversational AI tools play in how organisations engage customers and help co-create customer perceived value (Hollebeek et al., 2024).

More specifically, focusing on conversational AI tools and their application in the context of HEIs, studies explored their benefits in the education process once students have commenced their courses. Zhai and Wibowo (2023) and Ji, Han and Ko (2023) explored the application of conversational AI in language education as a collaborative partner to the human instructor and the improvements observed in university students' reading, writing, listening and interacting skills. Specific interest in the academic community has developed in relation to the potential unproven influences that LLMs, such as ChatGPT and others, have on the education process, the perception amongst students and the potential shifts in performance when these tools are deployed effectively (Ibrahim et al., 2023; Atlas, 2023; Klayklung et al., 2023). Pedagogical conversational AI tools are increasingly pervading classrooms as support tools for students when the ratio between the number of lecturers and students does not permit the provision of consistent and timely personalised attention and feedback to each student. In these circumstances CAs can provide an effective way to plug the gap and better meet the students' needs as demonstrated in the research of Chen et al. (2023).

Student recruitment can be viewed as a marketing communications task in the context of the education industry. Although studies such as Blümel, Zaki and Bohné (2024) and Hollebeek et al. (2024) explored customer engagement and outcomes in e-commerce terms, where purchases tend to be of lower value and have a shorter time span, they ignored the specific implications AI tools have in the context of a considered purchase and long-term commitment, such as the one a student makes when choosing a programme or a HEI to study for their degree. Similarly, studies such as Ibrahim et al. (2023) and Chen et al. (2023) explored the benefits conversational AI tools bring to students after they have commenced their course of study, there is little to no exploration of the factors leading to the adoption and usage of these tools prior to these students committing to an HEI. Therefore, the knowledge gap this research fills is at the intercept between these two underdeveloped areas where CAs can bring tangible benefits to both potential students and HEIs when deployed at the student recruitment part of the consumer journey.

In the extant literature on conversational AI, academic research usually follows one of two main approaches: the business implications perspective and the technological perspective.

The first approach examines how AI can influence businesses in three main directions: (1) augment and automate business processes, (2) provide insights contained in business databases for decision making and (3) offer new communication channels with customers and employees (Davenport and Ronaki, 2018; Huang and Rust, 2018, 2022; Dwivedi et al., 2021). Of the three potential AI uses listed above, the second and the third can be linked directly to research on CAs and are of greater interest to this research. The cognitive capability to provide valuable insights from data is based on utilising AI tools to analyse vast amounts of data and detect patterns that provide the basis for customisation and personalisation to groups or individuals, and thus predict future buying behaviour (Haleem et al., 2022; Rathore, 2023). Davenport and Ronaki (2018) highlighted the business use case for providing an alternative communication channel with customers and employees. Their study used NLP chatbots, based on ML technologies, that can provide 24/7 customer services, act as question-answering systems for customers and employees, and provide product and service recommendations that increase personalisation, engagement and sales (Deriu et al., 2021; Chandra et al., 2022).

The second approach is where AI and its various capabilities are explored from a technological perspective and viewed as an ecosystem for data collection and storage, statistical and computational algorithms, and output systems (Puntoni et al., 2021; Agrawal, Gans and Goldfarb, 2018). The data collection and storage capability is the process where customers make their personal information available to an AI algorithm. The AI algorithm uses its cognitive capability of “listening” to capture and store data about the individual and the environment in which they live (Puntoni et al., 2021; Grewal et al., 2022; Hu et al., 2022). The algorithm then uses its “judgement” capability to analyse the data, apply statistical models and generate predictions on the most likely outcome or next step, which in the world of marketing is also known as “classification”. The aim of classification is to create a hyper-personalised offering in order to increase engagement and customer satisfaction (Agrawal, Gans and Goldfarb, 2018; Kumar et al., 2019; Gao and Liu, 2022). Finally, the output system is linked to AI’s capability to act and, in the case of conversational AI, to engage in reciprocal communication with the customer (Puntoni et al., 2021).

Combining these two approaches, this research develops the recommendations provided in the research by Puntoni et al. (2021) which sets the scene of how CAs and their capabilities fit in the overall AI research agenda. More specifically, this research develops ideas derived from the future directions for specifically chatbot research proposed in a study by Følstad and 11 other researchers from the UK, Germany, France, Greece, Norway, The Netherlands and Italy (Følstad et al., 2021). The scholars proposed a research agenda that highlights the gaps in the existing literature and points to research areas that would allow for systematic knowledge creation. They detailed state-of-the-art knowledge, research challenges and future research directions for six research topics. The first two of these topics – “users and implications” and “chatbot user experience and design” – are the inspiration for this study. This study answers the call for further research investigating: (1) the “antecedents for chatbot use” (Følstad et al., 2021, p.2921), such as the motivations and behaviours in various user groups; and (2) the question of “how users perceive and respond to chatbots” (Følstad et al., 2021, p.2924) and, in particular, how chatbot design, layout and content can influence these perceptions.

This research directly takes up Følstad et al.’s (2021) first research challenge of defining the motivations and behaviours of specific user groups by investigating the context of student recruitment for HEIs. This decision was driven by the researcher’s experience of what is happening in the education industry, having worked in HEIs since 2014, as well as being directly responsible for the launch of chatbot technologies in a real-life context and being currently involved in the design and implementation of a new CA for the researcher’s employer. This research also presents a conceptual framework that provides further knowledge and guidance in determining how to meet the needs and expectations of these user groups. The conceptual framework resulting from the study also answers the second challenge posed by Følstad et al. (2021) by presenting a decision-making model on layout, design and content that aims to positively influence the perceptions and beliefs of these user groups.

The research questions are examined through the prism of two theories: the ELM (Petty and Cacioppo, 1986) and the UTAUT2 (Venkatesh, Thong and Xu, 2012). From the available theories relevant to the phenomenon of interest these two theories were most closely aligned with the research aim and objectives and they provide a lens through which the empirical data collected can be analysed to provide new insights into the researched topic. ELM is a model that provides a basis for the explanation of people’s attitudes, motivations and willingness to apply cognitive effort in processing persuasive messages, which directly links to the second and third research questions. For example, it was the model of choice for studies such as Chen, Yin and Gong (2023) and Michels et al. (2022) that investigated how AI chatbots can persuade customers to accept recommendations in an online shopping context. Similarly, Praditomo et al. (2022) combined the use of ELM and the technology acceptance model (TAM) to explain not only chatbot acceptance from a functionality perspective, but also from a social acceptance perspective; they referred to the combining of central and peripheral routes for chatbot design characteristics. Recommendations provided by HEI chatbots are considered "persuasive" messages; acceptance and trust in these messages are a central theme in this research, which makes ELM a suitable filter to analyse the empirical data collected from the participants.

UTAUT2, and its previous incarnations of TAM (Davis, 1987), TAM2 (David and Venkatesh, 2000) and UTAUT (Venkatesh et al., 2003), provides a framework to explain human behaviour specifically when interacting with technology and it aids analysis of the factors that influence the acceptance and use of technologies, such as culture and anthropomorphism. Since its inception in 2012, studies have judiciously applied this model to a wide variety of AI and conversational AI studies and they have sought to adapt it to the changing landscape of AI technological developments. Gansser and Reich (2021) proposed extending and updating UTAUT2 with five additional factors in view of AI's influence on everyday life environments and the behavioural intentions to use products containing AI algorithms in their design. More recently the behavioural intentions of using virtual assistants from a consumer's perspective were examined via the UTAUT2 lens by García de Blanes Sebastián, Sarimento Guede and Antonovica (2022); they added three more factors, namely perceived privacy risk, trust and personal innovativeness. Similarly, UTAUT2 underpinned the study of Wutz et al. (2023), which explored the factors that influence acceptability, acceptance and adoption of CAs in healthcare settings; as well as the study of Emon et al. (2023), who sought to understand the determinants that influence professionals' desire to adopt and use ChatGPT.

This research combines the topic of HEI marketing communication challenges with the ever-evolving state of emerging technologies, such as CAs, and positions them in the context of the phase of the student journey when prospective students are in the stage of information gathering and decision making about the course and university they will commit to. AI tools' cognitive skills, as described by Puntoni et al. (2021), of "listening" and "predicting" and behavioural skills of "communicating" and "recommending" are empirically tested in this study to establish the importance of each skill in the future development of CAs from the perspective of user experience and user types (Følstad et al., 2021). Objective 1 of the study seeks to establish the current status of research on the topic and to identify the gap in knowledge where the findings will bring most value and benefit to the discourse on the topic. Folstad et al.'s (2021) research direction 1a, "Emerging chatbot user groups and behaviours", and 2b, "Modelling and evaluating chatbot user experience", are addressed via Objective 2 of this study. Puntoni et al.'s (2021) framework of "listening", "predicting", "producing" and "interacting" is examined in the context of HEIs through Objective 3. The outcome of this research provides a conceptual framework to institutions that are ready to capitalise on the benefits that AI technologies provide, while being fully aware of the drawbacks that still exist due to the immature technology or attitudes of the people using them. This conceptual framework is linked to Objective 4 and is a direct answer to Folstad et al.'s (2021) research direction 2a, "Design for improving chatbot user experience".

1.6 Structure of Thesis

Chapter One introduced the background and current context of this study. The research problem, aim, objectives and research questions were defined and elaborated in light of the limitations of existing literature in the field of the student journey. The chapter also set out the rationale for the research by identifying a gap in the literature and the research problem explored. The rationale for the study was defined as effort to extend current knowledge in this research area.

The second chapter is dedicated to a critical review of the extant literature on the general field of AI followed by a more concrete exploration of conversational AI. Conceptual clarifications are offered in terms of what the terminology includes and how its definition has evolved over the years. This is followed by a summary of the most important CA taxonomies from the past five years. The review then shifts attention to ask how the student journey in HE is conceptualised. For the purposes of this study, the traditional student journey, which encompasses the time a student receives education, is combined with the concept of student recruitment, which is typically explored as a separate process, into a single conceptual model called the holistic student journey. Finally, two theories are proposed to act as a lens for the study's aim and objectives, namely the ELM (Petty and Cacioppo, 1986) and UTAUT2 (Venkatesh, Thong and Xu, 2012).

Chapter Three discusses the research design for this study. Firstly, the chapter elaborates on the interpretivist paradigm of social constructionism, which was selected for the study with the aim to capture personal experiences and motivations. The chapter explores the strengths and benefits of using narrative inquiry as the appropriate methodological approach, which incorporates elements of think-aloud protocols as well as semi-structured interviews. Then the chapter defends the choices made in relation to sample selection and sample size, and describes in detail the data collection method used. The final sections tackle the issues of researcher reflexivity, research quality and some ethical considerations in relation to this study.

Chapter Four explains the rationale for selecting thematic analysis as a data analytical method and its relevance to the concepts explored in this study. The six-step process is explained and its application in this research demonstrated in detail. The chapter presents an analysis of the four themes with their associated codes, which is followed by a detailed discussion on the factors relating to each theme and their connection with the overall topic of "purpose". The chapter provides a multitude of examples from the rich data collected during the chatbot experience of participants interacting with university chatbots and the interviews that followed.

Chapter Five develops the conceptual framework as a result this study. The framework refers to the four themes that emerged from the data analysis and connects them to the theoretical framework combining the two models used for analysis aiming to address the fourth research objective: "*To develop a conceptual framework comprising a structured decision-making process aimed at HEIs wishing to deploy CAs to enhance the student journey."* The chapter also contains a summary of key findings from the literature review about the methods by which the quality of chatbots is measured and the connections that can be made with the student journey.

Chapter Six consists of a brief conclusion to the study. The contribution of this research to theory and to practice is outlined. The practical implications and recommendations to HEIs' marketing communication strategies are considered. It also addresses some of the limitations of the study and suggests how future research can expand on the topics presented here.

A summary of the thesis structure is presented in Table 1.1.

Chapter Number and Name	**Key Sections**

Chapter One – Introduction	• Background • Research Problem • Aim, Objectives and Questions • Rationale for the Study • Structure of Thesis
Chapter Two – Critical Review of the Literature	• Conceptual Clarifications of AI • Taxonomies of CAs • Conceptual Clarification of Student Journey • Consumer Journey Mapping • Theoretical Frameworks
Chapter Three – Research Design	• Research Paradigm • Methodological Approach • Sample Size and Selection • Data Collection Method • Researcher Reflexivity • Research Quality • Ethical Considerations
Chapter Four – Analysis and Findings	• Rationale for Thematic Analysis • Major Themes • Discussion of Thematic Findings
Chapter Five – Conceptual Framework	• Importance of Purpose • Discussion on the Four Layers of the Framework • The Conceptual Framework
Chapter 6 – Conclusions and Recommendations	• Evaluation of Findings • Contributions to Theory • Managerial Contributions • Limitations of the Study • Future Research Directions

Table 1.1 Structure of Thesis (Source: Author, 2024)

1.7 Summary

This chapter provided an overview and background of the research study. The research aim, objectives and questions are defined and underpinned by the rationale for the study and theoretical frameworks. Additionally, the rationale of the study was clarified. The following chapter provides critical analysis of the existing literature, which will help the reader gain a deeper understanding of the main concepts and theories.

CHAPTER TWO
CRITICAL REVIEW OF THE LITERATURE

2.1 Introduction

The previous chapter provided the context and background of the issues examined in this research study, it defined the aim and objectives and formulated the research questions. It also outlined how this research intends to make a contribution to knowledge in the field of conversational AI in the context of student recruitment in HEIs.

This chapter embarks on a critical literature review of existing knowledge and provides conceptual clarifications on the topic of AI in general, and the topic of conversational AI more specifically because it is the main technology behind chatbots. An exploration of the current state of chatbot typologies is presented via a detailed and historically ordered taxonomy. The concepts underpinning student journey and student recruitment in HEIs are explored; in particular, issues around a holistic student journey are presented based on the theoretical foundation of the customer journey mapping techniques used in marketing-related research. Theoretical underpinnings relevant to this research topic are explained and linked to each other.

2.2 Conceptual Clarifications

2.2.1 Conceptualisation of AI

Currently, AI is one of the most fashionable but at the same time most ambiguous terms of the modern age (Fortuna and Gorbaniuk, 2022). AI is fashionable because AI-powered tools have pervaded every area of our life, as individuals, as consumers, as employees, as well as core industries, such as manufacturing, logistics, healthcare, retailing, banking, agriculture, education and marketing. AI tools have been adopted in business functions of customer service, human resource management (HRM), operations and even strategic planning. The term AI can also be described as ambiguous when one considers that the definition of what falls under the AI umbrella seems to change and evolve rapidly with every new technological advance. In its nearly 70 years of history, definitions of AI have evolved as the goalposts of what constitutes human intelligence have moved, and they reflect the ever-increasing capabilities of computing machines to mimic human cognitive abilities in mechanical computation, thinking and, more recently, feeling (Huang and Rust, 2018, 2022).

2.2.1.1 Fashionable AI

A prolific body of academic research focuses on AI in a multitude of industries, which illustrates the first assertion that AI is fashionable. In banking and finance, for example, researchers have explored: disruptive technologies such as Internet of Things, blockchain, VR and AI in the context of emerging markets and developing economies (Omoge, Gala and Horky, 2022; Arjun, Kuanr and Suprabha, 2021); “digital natives”’ perceptions of these disruptive technologies and their attitudes towards mobile banking (Payne, Peltier and Barger , 2018; Wu and Ho, 2022; Putri and Ginting, 2021); and, more generally, how chatbots influence customers’ brand perception and engagement (Hari, Iyer and Sampat , 2021; Trivedi, 2019).

A review of the medical literature by Vaishya et al. (2020) concluded that the COVID-19 pandemic propelled the adoption and use of AI tools in medicine and healthcare in seven different areas of application ranging from contact tracing to medicine discovery, to monitoring of treatments. Another stream of study focuses on current issues including: the ethical implications of using AI in hospitals (Saheb, Saheb and Carpenter, 2021; Mirbabaie et al., 2021; Siala and Wang, 2022); the shift from a doctor-centric to a patient-centric approach facilitated by patient data collected by AI-powered devices, such as smart wearables (Haleem et al., 2022; Nasr et al., 2021); the explainability and causality of AI algorithms that create “explainable medicine” (Holzinger et al., 2019; Malik, Pathania and Rathaur, 2019); and the exploration of chatbots that aim to reduce the impact of COVID-19 on the mental health of people through text and voice interactions (Zhu et al., 2021; Zhu, Wang and Pu, 2022).

Agriculture has been interested in the implementation of AI technologies for several years, for example: the tasks of optimising irrigation and the application of pesticides and herbicides (Talaviya et al., 2020; Sinwar et al., 2020); and the potential pitfalls of this technology from an ethical perspective when inaccurate AI predictions may lead to loss of harvest or livestock (Ryan, 2019). From the perspective of sustainability and meeting the European Union’s (EU’s) climate and biodiversity targets, digitalisation and AI-driven smart agriculture play a pivotal role in achieving these targets while considering issues with data privacy access and security (Garske, Bau and Ekardt, 2021; Martos et al., 2021). Similarly, Benjamin and Foye (2022) posed the same questions in the context of agriculture in Africa, more specifically, Nigeria.

Military decision making has been aided by computing machines since World War II. The warfare application of AI has been one of the main drivers of the research and development of AI-powered technologies (Rasch, Kott and Forbus, 2003; van den Bosch and Brokhorst, 2018). In modern conflicts, warfare has moved to cyberspace where military campaigns are fought digitally and the state of AI development on a national level is the determining factor of who is the dominating power (Johnson, 2021; Kania, 2019). The weapons of choice today are misinformation, deepfakes, analysis of large quantities of social media feeds to determine the position of the enemy, as we have seen in the recent Russia–Ukraine war, or the deployment of autonomous machines such as drones (Horowitz, Kahn and Samotin, 2022).

E-commerce and retail have been experimenting with AI technologies both online and in physical stores. Smart algorithms are embodied and anthropomorphised (Klein and Martinez, 2022) to elicit a greater emotional response, greater trust and easier acceptance by customers, especially when they are asked to share personal information (Wang et al., 2022; Song and Kim, 2021, 2022; Rese, Ganster and Baier, 2020). Noble et al. (2022) went as far as to say that the harmonious interaction between humans and machines is triggering the Fifth Industrial Revolution, which is described as a reality where digital, physical and biological technologies merge and enable enhanced well-being for societal actors. The emerging challenges and opportunities for retail and e-commerce in the metaverse are also beginning to emerge in academic research; the research is refracted through the lens of business capabilities and readiness to utilise and embrace a new channel in cyberspace, the digital supply chain (Yawised, Apasrawirote and Boonparn, 2022; Ageron, Bentahar and Gunasekaran, 2020). Chatbots in retail are compared to other AI tools, such as AR, and their effectiveness from a customer attitude, engagement and acceptance perspective was investigated by Moriuchi et al. (2021) as well as by Jiang, Qin and Li (2022) who evaluated chatbots through the lens of social presence theory and concluded that they exert a direct and positive impact on the retailer’s image.

The field of education does not fall behind other industries when it comes to the adoption and use of AI-powered technologies. In particular, AI tools have found a place in areas such as personalising the teaching and learning experience, skills development, collaborative learning, and assessments (Dhawan and Batra, 2020; Cope, Kalantzis and Searsmith, 2021). Most AI technologies powering what have been dubbed as “pedagogical agents” are based on a strand of AI known as conversational AI. Conversational AI allows for communication between students and machines through either text or voice (Pérez-Marín, 2021; Sikström et al., 2022; Ceha and Law, 2022). Chatbots’ effectiveness in assisting students to learn a foreign language through providing hard-to-find opportunities for conversational exposure was the focus of research by Divekar et al. (2021), Pérez, Daradoumis and Puig (2020) and Vázquez-Cano, Mengual-Andrés and López-Meneses (2021); while Ferrell and Ferrell (2020) stated that marketing education will greatly benefit from incorporating this technology, particularly because a large part of the marketer’s job has moved from creative to analytical tasks. Chatbots can also be deployed as virtual teaching assistants in a classroom where the number of students is large and the teacher is unable to provide personal attention to every student in a targeted and personalised way; in this situation, bots take over the routine repetitive tasks allowing the humans to provide quality education at a higher cognitive level (Dimitriadis, 2020; Bhutoria, 2022). The benefits of virtual teaching assistants include: (1) improving access to good educational materials to students who may not otherwise be able to participate in education in parts of the world where there is a shortage of schools and good teachers (Sadiku, Musa and Chukwu, 2022); (2) the provision of automated grading where knowledge is assessed and analysed against a pre-set database of answers, and generating feedback and recommendations for further study and a personalised development plan for the student (Owoc, Sawicka and Weichbroth, 2019); (3) the task of revision can benefit from an AI tool that is trained in tracking the learning journey and prompting students to engage in “intermediate spaced repetition”, which aims to analyse when a student is most likely to forget something and recommending them to revise (Owoc, Sawicka and Weichbroth, 2019); (4) educators can benefit from instant access to additional information to aid the creation of a curriculum that enhances students’ knowledge and understanding not just by providing an answer to a question but also the logic of why a conclusion was reached (Crowe, LaPierre and Kebritchi, 2017); (5) the creation of “adaptive gamification environments” where game-based learning provides learners with opportunities to interact with intuitive algorithms that serve the student with targeted educational materials and revision opportunities and, at the same time, lower development costs for educational institutions (Bennani, Maalel and Ben Ghezala, 2022).

As a business function, marketing is one of the pioneers in the adoption of AI tools both at the back end for analytical and decision-making purposes and at the front end of marketing campaigns where marketing communication is key for the brand equity of organisations. Jarek and Mazurek (2019) identified five main areas of application – voice processing, text processing, image recognition, decision making and autonomous robots – and analysed their impact on the marketing mix; they also analysed the nature of the role of the marketer in today’s technologically enabled work environment. The next seven paragraphs describe each of the seven Ps (product, price, place, promotion, people, process and physical evidence) of the marketing mix in turn.

In the context of “product”, the theme of personalisation appears strongly with the new term of “hyper-personalisation”. Hyper-personalisation has been piloted across many services and industries both in web and mobile marketing (Chandra et al., 2022; Tong, Luo and Xu, 2020; Kumar et al., 2019). Huang and Rust (2021) went further and put personalisation (thinking AI) as one of the pillars of a new strategic framework for applications of AI in marketing. The pillars of personalisation (thinking AI), standardisation (mechanical AI) and renationalisation (feeling AI) support the marketing decision-making process through strategic tasks, such as segmentation, targeting and positioning. The pillars also support tasks relating to marketing research, such as data collection, market analysis and customer understanding. Another application of AI relating to product and services is the area of automated recommendation systems, which take over complex, time-consuming and uncertain parts of the consumer experience, such as searches for the best product or deal (Lemon and Verhoef, 2016). These systems can be further classified as “content-based”, where users receive recommendations based on an initial set of declared preferences, and “knowledge-based”, which is used for decisions requiring higher involvement from the customer. Knowledge-based systems combine customer preferences with content filtering to provide more accurate knowledge of customers’ opinions and they continuously improve the quality of the recommendations provided (Klaus and Zaichkowsky, 2020).

In the area of “pricing”, AI tools have been used for several years to power dynamic pricing strategies where demand, together with information already collected on the customer, determines the price offered; this type of pricing is used in the airline industry (Shukla et al., 2019), electricity retail (Das et al., 2020), car loans (Arevalillo, 2019), hotel room bookings (Bigne, Nicolau and William, 2021), and retail customer interactions (Stone et al., 2020). The type of AI technology powering these pricing algorithms is predictive analytics, which forecasts which customers are likely to convert, the propensity and at what price, and it also estimates trends in customer behaviour (Nair and Gupta, 2021). The primary benefits of applying predictive analytics in digital marketing include: (1) improving knowledge about customers, (2) identifying online actions that improve offline decisions, (3) optimising communication frequency, (4) improving lead scoring and conversion, and (5) maximising profits (Campbell et al., 2020).

AI technologies are also used in the “promotion” activities of brands for strategic decision making and social presence (in the form of chatbots, virtual assistants and CAs). Social media channels are a prime example of the utilisation of such technologies where analytical tools are used to prioritise which social media users to respond to, analyse their online behaviour and social media identity, and to model that behaviour and predict future behaviour (Overgoor et al., 2019). Social presence in social media channels is considered an important factor that brings positive benefits when brands look to create relationships with their customers. Social presence is often achieved through the deployment of chatbots that aim to mimic real human conversation through embedded personality and social cues (Liu, Lei and Law, 2022). The data collected from these chatbot interactions can then be used to elicit and monitor customers’ needs and to predict trends; this allows organisations to tailor their offerings and provide instant feedback and personalisation at a scale not possible before (Kühl, Mühlthaler and Goutier, 2020; Nanayakkara, 2020). Campbell et al. (2020) took the discussion a step further and proposed that AI tools can assist marketers not only by analysing the current situation and providing information on the customers and the marketplace, but also by helping to develop product, pricing, promotion and place strategies and guide the objectives of future marketing campaigns.

The automation of the sales and distribution channels, that is “place”, has also benefited from the application of AI tools in the form of hybrid retail channels where customers are guided by technology to the best product that meets their needs through recommendation algorithms made available through electronic devices or embodied robots (Wang et al., 2022; Song and Kim, 2022). In the space of personalised recommendation systems, we see the full power of AI-powered tools in global players such as Amazon and Netflix; they utilise customer preferences data and combine it with data from similar customer micro-segments to create a unique selection of recommendations for each individual customer (Huang and Rust, 2021; Guo et al., 2018; Dekimpe, 2022). AI tools have also found their place in the business-to-business (B2B) space, albeit not to the extent they have penetrated the business-to-consumer (B2C) space (Keegan, Dennehy and Naudé, 2022; Dwivedi and Wang, 2022); this can be explained by the fact that even though AI is exceptional at extrapolating future trends from past events (Davenport et al., 2020), it is still unable to adapt to the complexities of a business scenario (Dwivedi et al., 2021). The choice of distribution channels available to marketers has also changed with the popularisation of virtual assistants, which take over some routine shopping decisions on behalf of the customer; therefore, distribution strategies must aim to make products attractive to this intermediary instead of the final consumer of the product (Maarek, 2018).

The success of brands in the modern marketplace is closely linked to the quality of “people” that organisations can recruit and retain to represent them in front of customers, suppliers and other stakeholders. While external branding is aimed at potential and existing customers, internal branding has historically been the domain of the HRM department (Barros-Arrieta and García-Cali, 2021). There are both proponents and doubters about the application of AI tools in HRM. AI tools are used from the first stage of the human resource cycle: the hiring process. Li et al. (2021) examined two stages of algorithmic hiring practices: sourcing and assessment. They found that AI tools brought efficiencies to both stages when processing candidate data, which allowed for a larger number of applications to be analysed from a broader and more diverse pool of candidates. However, these tools are mistrusted due to concerns about data accuracy and their inability to create unbiased matches between candidates and available roles (Lee, 2018; Kasinidou et al., 2021). Further into the HRM cycle there is evidence of AI-enabled tools to aid organisations in their enhancement of employee satisfaction, engagement and retention (Malik et al., 2021). This is achieved by: providing knowledge-sharing systems that can be personalised to an individual’s needs and interests; monitoring and improving organisational productivity and personnel performance, which leads to cost savings by effectively balancing motivational factors such as overall workload with work stress and job security (Azadeh and Zarrin, 2016); or evaluating the training effectiveness of employees and analysing factors such as training utilisation, affect, performance and financial impact (Sitzmann and Weinhardt, 2019).

One of the areas where AI has had a profound effect in the way marketing activities are conducted is the field of marketing automation. Marketing “processes” have been transformed in relation to how social media is managed and, in particular, the algorithmic purchasing of social media exposure, the customising and personalising of social media campaigns, content curation, the selection and adjustment of targeted micro-audiences and the capture of customer data (Benabdelouahed and Dakouan, 2020; Schwartz and Ungar, 2015; Tuten and Hanlon, 2022; Scott, 2022). Beyond social media, AI tools are automating or, in some cases, augmenting the more routine and repetitive tasks marketers are expected to perform in customer relations, CRM and email marketing (Raisch and Krakowski, 2020; Libai et al., 2020; Kar and Kushwaha, 2021)

Industries such as hospitality, education and retailing are major examples of where marketing employs AI tools in a “physical and tangible form” through virtual spaces or intelligent robots. For example, fashion sales robots are used to share information in customer service settings and in return customers share personal information with the retailer (Song and Kim, 2021; Wang et al., 2022). Another example is retailers’ use of intelligent delivery robots in the last mile of their delivery service; drones or smart lockers are available to organisations prepared to embrace and implement AI-powered tools (Buldeo Rai, Verlinde and Macharis, 2019; Vakulenko et al., 2019; Tsai and Tiwasing, 2021). Other industries with a multitude of examples globally are hospitality and tourism. Initially, AI tools were simply embedded in machines such as self-service kiosks at fast food restaurants (Rastegar et al., 2021; Chi and Nam, 2022), where some of the routine tasks could be automated without the need of a human to provide emotional understanding or a connection with the customer. With the advancement of AI tools over time, AI-powered robots were increasingly utilised to deliver more personalised customer experiences, such as to guide tourists around art galleries or museums, robotic bartenders serving drinks or a robotic waiter bringing room service in the morning (Singh and Atta, 2021; Manthiou and Klaus, 2022; Orea-Giner et al., 2022). In today's hospitality environment, AI tools are used in much broader and unstructured environments, such as image and facial recognition in border control, semi-autonomous vehicles in tourist attractions or chatbots embedded in customer service robots trained to respond both to text and voice inputs (Ivanov and Umbrello, 2021).

The examples thus far demonstrate that AI can be considered a current and "fashionable" concept. It is no longer a notion from the realm of science fiction or the narrative of futurologists, but an integral part of many business models and a key strategic element in the planning of organisations in medicine, finance, agriculture, e-commerce and education (Dwivedi et al., 2021).

2.2.1.2 Ambiguous AI

To begin the quest of understanding why AI is dubbed "ambiguous" (Fortuna and Gorbaniuk, 2022), it may be useful to try to define what AI is not; however, even that is a difficult task due to the evolutionary nature of the technology. One of the most frequently quoted expressions summarising this dilemma comes from Crawford (2021, p.7), "AI is neither Artificial nor Intelligent". The basis of this assertion can be traced back to the work by Dreyfus (1972) who, in his critique of artificial reasoning, concluded that we change our definition every time there is a technological advancement, and that at any given time AI is basically “what computers can’t do” yet. This is known as the “AI effect” (Haenlein and Kaplan, 2019), which summarises the notion that we may consider something to be AI only until we see that a machine can perform the task and, consequently, we no longer think of it as AI. The “AI effect” makes the task of defining AI quite difficult and ambiguity will always be a companion in these endeavours.

Looking back through history, valiant efforts have been made to tackle this challenge. The birth of AI and cybernetics research can be traced back to the 1940s, 1950s and 1960s. In 1943 McCullogh and Pitts combined neuroscience and mathematical and logic concepts into a model of “artificial neurons” capable of performing basic computation and even learning (McCullogh and Pitts, 1943). The topic was further popularised in the 1950s when Alan Turing (dubbed the father of AI) asked the question “Can machines think?” and introduced the concept of the Turing test to the general public (Turing, 1950). Widespread AI research began in 1956 when 10 leading US scientists were invited to participate in the Dartmouth Summer Research Project on Artificial Intelligence. This is where it is believed that the term “artificial intelligence” was used for the first time; so, it can be said that this was the birthplace of the scientific discipline (Russell and Norvig, 2022). Early attempts to define what AI actually encompasses, considering the limited computing power and the uncertainty of how to achieve the goal of intelligence, were quite fuzzy. McCarthy and Minsky proposed in 1955 that the field of AI is concerned with “making a machine behave in ways that would be called intelligent if a human were so behaving” (McCarthy et al., 1955, p.13). Minsky (1968, p.v) confirmed this view with the addition that he now called the field of AI as part of the sciences and defined it as “the science of making machines do things that would require intelligence if done by men”. Both definitions demonstrate a lack of understanding of what human intelligence comprises and how it can be represented in mathematical terms so it can be coded and understood by machines. Notably, in that period, the economist and sociologist Herbert Simon prophesised in 1957 that AI would succeed in beating humans in chess in the next 10 years (Simon, 1957).

However, that was not to be the case as in the 1970s AI entered a period of “AI winter” (Yang, 2006) when interest and research in the topic waned. It was not until the 1980s and 1990s that AI became popular with researchers again with the popularisation of a branch of AI called “expert systems” (Smith et al., 2006). Bar and Feigenbaum (1981, p.306) in their definition of an expert system finally attempted to define which aspects of human intelligence people would try to emulate in machines: “systems that exhibit the characteristics we associate with intelligence in human behaviour – understanding language, learning, reasoning, solving problems and so on”. Then Stevens (1984) and McKinion and Lemmon (1985) elaborated on the characteristics of the machines: “A true Expert system not only performs the traditional computer functions of handling large amounts of data, but it also manipulates that data so the output is a meaningful answer to a less than fully specified question” (Castillo, Gutierrez and Hadi, 2012, p.2) and “Expert Systems are special computer software applications that are capable of carrying out reasoning and analysis functions in narrowly defined subject areas at proficiency levels approaching that of a human expert” (McKinion and Lemmon, 1985, p.31). In both definitions we see concrete tasks and expectations being added to the definition of the field so that the boundaries of what is included and what is excluded can be more precisely drawn. A notable feature is the aspiration to reach the level of intelligence of a human expert and not necessarily to surpass it, which was a notion that lay outside the imagination of researchers of that time. Buchanan et al. (1988, p.23) summarised the developments achieved in the period by describing how machines reason and the methods they use: “An expert system is a computer program that reasons with knowledge that is symbolic as well as mathematical, uses methods that are heuristic (plausible) as well as algorithmic (certain), performs as well as specialists in its problem area, makes understandable what it knows and the reasons for its answers, and retains flexibility”.

Since around 2010, the barriers that caused the AI winter of the 1970s started to lift. The invention of new technologies tackling memory, computing power and availability of data helped to bring about the next “summer” in terms of investment, research and popularity of the topic. The present day is a period of heightened interest from both academic and industrial circles looking to utilise the technological advances we have seen in the past 70 years (Kaplan, 2022). The definitions of AI from the last two decades reflect the increasing complexity of the world and the need for intelligence to perform in different environments: “artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment” (Nilsson, 2009, p.xiii); and, more recently, Russell and Norvig (2022, p.35) confirmed the importance of this skill: “machines that can compute how to act effectively and safely in a wide variety of novel situations”. The evolving techniques of computation are captured in the definition offered by Poole and Mackworth (2010, p.3): "the synthesis and analysis of computational agents that act intelligently". The fascination with the human mind and human intelligence as the model and benchmark for machine intelligence continued in 2018 as shown in the definitions offered by Wang, Liu and Dougherty (2018) and Huang and Rust (2018) with Longoni, Bonezzi and Morewedge (2019, p.631) extending the definition with notions of "perceptual, cognitive, and conversational functions of the human mind". The ability of algorithms to learn was first included in definitions by Kaplan and Haenlein (2019, p.15), "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" and by Duan, Edwards and Dwivedi (2019, p.2), "It is normally referred to as the ability of a machine to learn from experience, adjust to new inputs and perform human-like tasks". Zhang and Lu (2021, p.1) brought us full circle back to the challenges when attempting to define AI and acknowledged the fact that what was considered AI in the past ceases to be the case when machines prove they are capable of completing the task: "Artificial intelligence is the study of how to make computers perform intelligent tasks that, in the past, could only be performed by humans".

From the range of definitions collated above several concepts emerge that seem to repeat throughout the decades of research: (a) machines "behaving" or "acting" as humans (i.e., sense of agency); (b) machines perform "perceptual", "cognitive" and "conversational" functions (i.e., functions of the mind); (c) "learning" from data and experiences (i.e., evidence of intelligence).

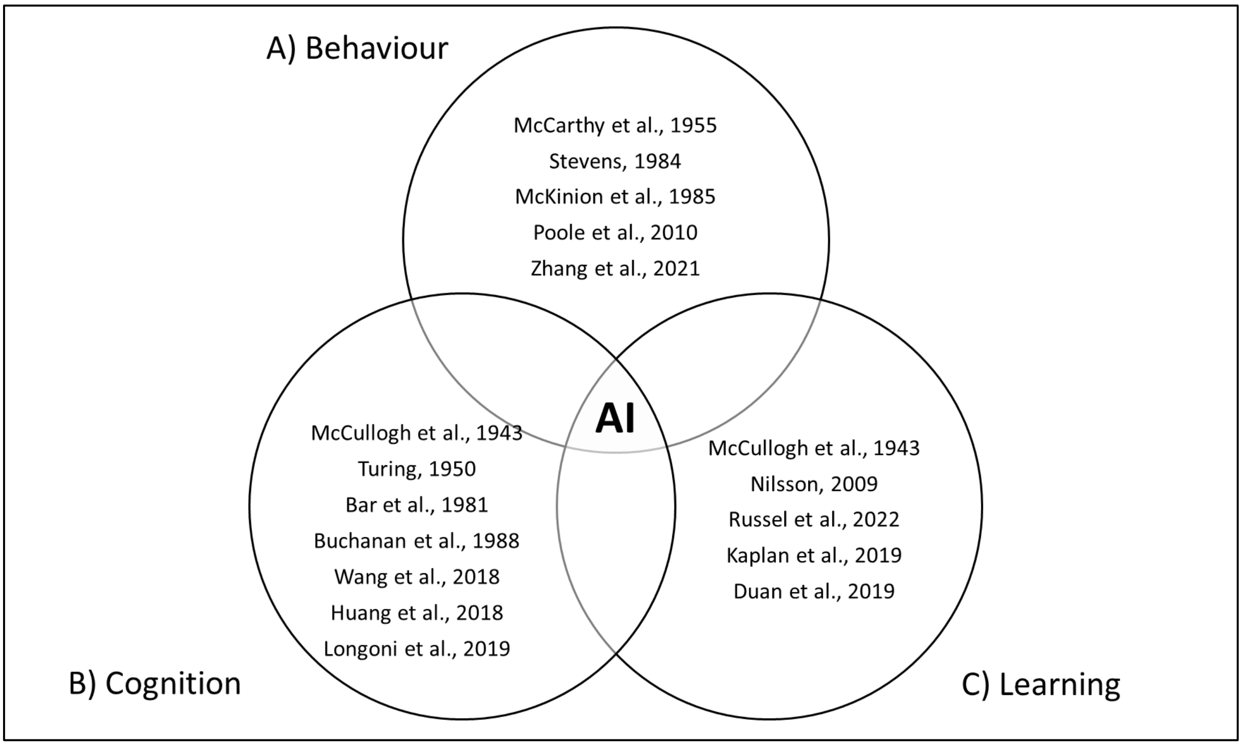

Figure 2.1 Definitions of Artificial Intelligence (Source: Author, 2024)

All three concepts are essential for businesses to embrace for the successful deployment of AI tools in industry, marketing and education; the skill of conversation, which combines agency, cognition and intelligence, is of particular interest to this research project. Recent developments in these concepts have been captured and analysed by Stanford University's One Hundred Year Study on AI, known as AI100; AI100 provides scientific insights into the current state of AI and its capabilities in relation to behaviour, cognition, perception, conversation, decision making and learning (Littman et al., 2021).

From a more technical perspective, the current capabilities of AI can be classified in eight broad categories: (1) computer vision – image, (2) computer vision – video, (3) language, (4) speech, (5) recommendation, (6) reinforcement learning, (7) hardware and (8) robotics (Zhang et al., 2022).

The aim of this study is to explore the capabilities of “language”, “speech” and “recommendation”. “Language” refers to the AI subfield of NLP which tackles several tasks across the language domain, such as language understanding, text summarisation, sentiment analysis and machine translation. “Speech” refers to the language tasks of recognising human speech and identifying the meanings of words, converting them into text and responding using synthesising human-like speech. “Recommendation” is the specific task of suggesting items or services that may be of interest to users, such as movies to watch, articles to read or products to purchase (Zhang et al., 2022). The strengths and limitations of these three capabilities provide the foundations of conversational AI tools that marketers must consider when creating a chatbot framework, strategy for implementation and general AI policies for their organisations.

For much of its 70+ years history, AI has been incrementally advancing; however, these developments have been achieved in very narrow fields and for individual tasks. That is why it is said that today we have “artificial narrow intelligence” (Kaplan and Haenlein, 2019); the first generation of AI applications are limited to one or a small number of similar tasks in a predefined domain thanks to advances in ML, deep learning and NLP (Huang and Rust, 2021; Jarek and Mazurek, 2019; Malone, 2018). Research is being conducted in the development of the next generation of AI, which is called artificial general intelligence or “singularity”. Artificial general intelligence will have the capability to plan, reason and autonomously solve problems in tasks it was never designed to do (Monett, Lewis and Thórisson, 2020; Kaplan and Haenlein, 2019; Wang, Liu and Dougherty, 2018). Perhaps, even further into the future, an artificial super intelligence will emerge that is self-aware and conscious, possessing general wisdom, capable of scientific creativity and social skills; thus, fulfilling Alan Turing’s vision of machines that can think (Carrillo, 2020; Welsh, 2019; Gill, 2016; Turing, 1950).

There is not one universal definition of AI accepted across academia, industry and government (House of Lords, 2018). For example, the European Parliament’s most recent definition of AI is “the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity” (European Parliament, 2023a, p.2). However, this diversity in definitions should not be considered a limitation to the exploration of the field, but rather an opportunity for research to contribute clarity and definition to new use cases where AI technologies are being deployed. One such use case is conversational AI: a narrow strand of AI concerned with communication tools that allow human–computer interaction (Yan, 2018; Lester, Branting and Mott, 2004).

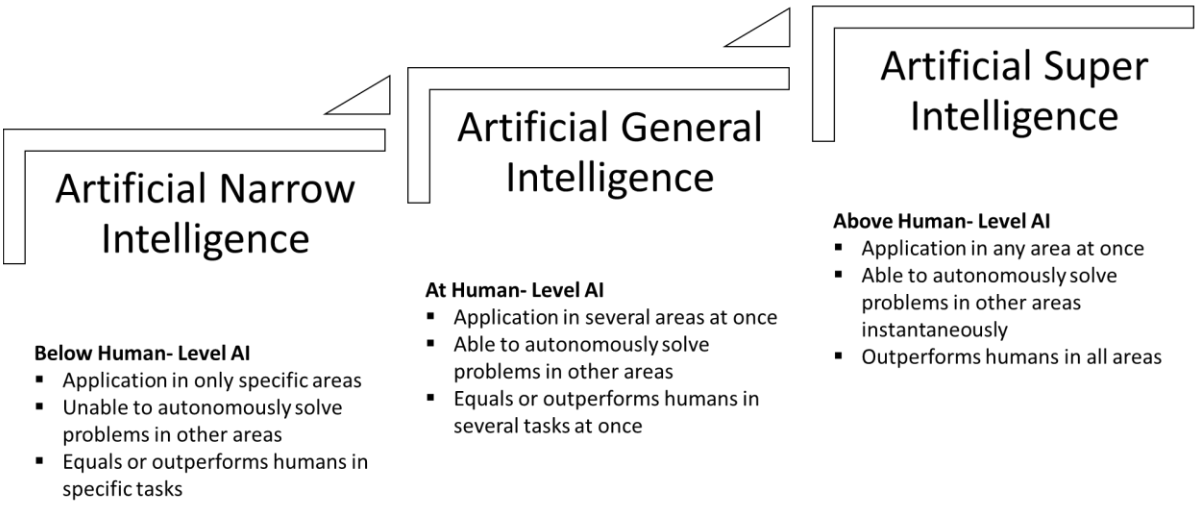

Figure 2.2 Stages of Artificial Intelligence Development (Source: Author, 2024)

2.2.2 Conceptualisation of Conversational AI

Conversational AI is an umbrella term for a variety of technologies that allow for humans to interact with computers usually over the internet (Gardiner and Smith, 2021). Early academic research (in 2015 and 2016) on CAs from various industries placed a particular emphasis on defining the concept of natural language. In medicine, for example, Comendador et al. (2015, p.137) described a paediatric medical consultant bot as “a conversational agent that interacts with users, turn by turn using natural language”, while Miner et al. (2016, p.619) defined smart phone-based mental health bots as “computer programs designed to respond to users in natural language, thereby mimicking conversations between people”.

The birthyear of the modern chatbot is widely considered to be 2016, which is when Facebook launched the first free commercial chatbot in Messenger and researchers such as Dale (2016) and McTear, Callejas and Griol (2016) began to equate a conversation with a CA to one with another human being. Dale’s definition (2016, p.811) of intelligent virtual assistants is software that “achieve some result by conversing with a machine in a dialogic fashion, using natural language”. McTear, Callejas and Griol’s definition (2016, p.619) of “people interact with intelligent systems using natural language, just like engaging in a conversation with another human being”. Both definitions represent the aspirations of the time to create conversations that feel real, easy and natural. However, conversations became more real, easier and more natural only with advances in ML and deep learning (Yan, 2018) when conversations became “experiences that mimic conversations with real people” (Deloitte, 2019, p.4) and “interacting with users through natural language as in human-to-human conversations” (Diederich, Brendel and Kolbe, 2019, p.1100).

This enhanced view of CAs was only possible due to the availability of large amounts of training data that allowed the models to more accurately recognise and synthesise human speech as well as translate meaning across multiple languages (IBM, 2020; Vishnoi, 2020).

In 2021, 12 European scholars conducted a seminar on conversational AI involving over 150 individuals from 30 countries and collectively agreed on a definition that defines CAs as “agents providing access to information and services through interaction in everyday language” (Følstad et al., 2021, p.2916). This definition widens the scope to include CAs for goal-oriented task completion, information gathering, entertainment and social interaction. It also captures CAs’ capabilities to interact via text, voice or both.

In recent academic research the definition of CAs has been widened to include terms such as “virtual assistants” and “digital assistants”. This more complex and sophisticated technology relies on the interplay of three key elements: (1) the individual user, who seeks to achieve certain goals; (2) the tasks the user needs to accomplish so as to achieve their goals; and (3) the technology, such as the computer system (i.e., software, hardware and data) that an individual may interact with to carry out tasks (Maedche et al., 2019). Users can approach these assistants with a variety of requests: to answer questions, complete tasks or even to just have social interaction in the form of a joke or a playful request (Shani et al., 2021). Virtual assistants begin to match our expectations of a natural human-like conversation when they are designed on the basis of LLMs, such as GPT-3, and are able to conduct open-topic conversations with strong interpersonal skills and the resemblance of personality (Brown et al., 2020). As of January 2023, the most disruptive and innovative of these language models is ChatGPT (GPT-3.5); ChatGPT has the ability to generate unique text on any suggested topic, from complete paragraphs to short essays, increasing the perception of personality and consciousness among the users of the model (Haque et al., 2022).

In many publications the terms “chatbot”, “conversational agent” and “virtual assistants” are used interchangeably. However, it is useful to make some distinctions between them as their application differs from both a consumer and an organisational perspective. According to Gao, Galley and Li (2019), the difference between the three terms can be described as:

a) CAs are “question-answering” models that are programmed to provide concise and direct answers to users’ questions. These answers are generated from large databases containing a variety of online information sources, such as the web, a company’s proprietary information such as sales and marketing reports and databases purchased from third parties.
b) Virtual assistants are “task completion” models designed to perform specific actions to achieve a predetermined goal requested by the user, such as booking restaurant reservations, tracking a package or updating calendar schedules. The most popular representatives of this group are the personal assistants marketed by Apple (Siri), Amazon (Alexa), Google (Home), and Microsoft (Cortana).
c) Chatbots are conversational models designed for social interactions. They need to be able to converse with their counterparts seamlessly and appropriately, and in a manner that resembles human conversation as closely

as possible. The programming needs to be very wide in the scope of topics as conversations can take any direction. An example of a social companion is Replika, which was designed to become your virtual best friend and mimic the existence of emotions and empathy.

Of the three types described above, businesses and education institutions most often invest in “question-answering” models or CAs closely linked to one of the stages of their customer or student journeys (Khosrawi-Rad et al., 2022). The idea of such programmes dates back to the 1960s with the invention of the first chatbot ELIZA by Joseph Weizenbaum (1966); ELIZA was designed to perform a basic conversation with hospital patients in the role of a councillor. Since then, the technological advances in ML, NLP as well as the advent of powerful connected devices have significantly enhanced the capabilities and potential of CAs; these advances have driven the evolution of CAs from rule-based models to agents that utilise AI in their processes (Knijnenburg and Willemsen, 2016).

The rule-based models are pre-programmed by humans with direct and unambiguous instructions on how to handle every possible query that a customer may have. They resemble a cooking recipe where all the ingredients are known and at the right quantities, and the process has very precise steps of how to put them together to produce a predictable outcome (Fry, 2019). Since all the parameters and constraints of the programming are pre-mediated and conceived by a human coder, they are also easy to comprehend and explain. Therefore, rule-based algorithms are also called “interpretable” (Wahde and Vigolin, 2022). Being interpretable, however, should not be confused with lack of complexity, because some rule-based CAs are as sophisticated as some ML-based agents; the main difference between rule-based algorithms and ML-based agents is that with rule-based CAs the logic for reaching a particular decision can be explained and mapped utilising the typical programming rules of IF-THEN-ELSE or sorting and filtering functions (Hong, Hullman and Bertini, 2020).

ML models mimic the process of how the brain is structured and operates; they rely on the connections between nodes (much like synapses in the brain) that get stronger the more times a decision is made and, thus, cause the process of learning to occur (Russell and Norvig, 2022). These models rely on many examples from the past where through either supervised, unsupervised, semi-supervised or reinforcement learning, the algorithm detects patterns and clusters and extrapolates the most plausible answer to a question (Diederich, Brendel and Kolbe, 2019). When the algorithm produces an answer, it is impossible to know by what process the decision was made that this was the most probable answer (Rai, 2020). That is why these algorithms are often called “black boxes”, which has given rise to a new ethical strand of AI called “explainable AI”.

NLP is a branch of ML that is particularly important in conversational AI. NLP refers to the algorithm’s capacity to process human speech, whether written or spoken, and translate that to a computer language that can perform various statistical and semantic manipulations; the purpose is to firstly understand the meaning of the sentence and secondly to construct a response in a form that a human would comprehend (Shankar and Parsana, 2022). In the domain of marketing, NLP models are often used to analyse text from sources such as online browsing records, recorded conversations, email communications and social media chatter (Berger et al., 2020; Hartmann et al., 2019; Hovy, Melumad and Inman 2021).

Today, both rule-based and ML-based CAs are in wide use by organisations around the world. Each of these approaches has unique benefits and limitations. Rule-based algorithms are coded by humans and therefore are easy to understand and interpret; anyone can "open them up" and see how they work under the bonnet (Fry, 2019). However, their logical construction is also the source of their limitations, for example, they can only solve problems for which a human knows how to write specific instructions. Due to this limitation, rule-based algorithms are less able to adapt to the context from which users are drawing their enquiries and thus are unable to provide personalised answers, especially when we explore use cases in customer services (Gnewuch, Morana and Maedche, 2017). CAs are often viewed as more than just a company resource, they are expected to take an active part in customer interactions and thus become actors in the organisation's value creation process (Wang, Teo and Janssen, 2021; Mygland et al., 2021).

ML algorithms are better suited to solving more complex problems in which typically human judgement would be expected to play a central role. For example, insurance companies use bots to communicate with customers in relation to damages and claims, and they are able to pick up on emotions such as anger or irony (Wuenderlich and Paluch, 2017). ML algorithms allow capabilities to be developed over time and thus they can provide the conditions for self-learning platforms that improve over time (Diederich, Brendel and Kolbe, 2019).These capabilities often come at the expense of complexity, which not only makes the algorithms hard to train as they require copious amounts of past data, but also turns the models into black boxes where transparency of how a decision was reached is lost in the depths of the algorithm (Rai, 2020; Adadi and Berrada, 2018, Hong, Hullman and Bertini, 2020).

2.2.3 Conceptualisation of Integrated Marketing Communications and AI

Having demonstrated the influence AI has on each of the seven Ps of marketing, and defined what is within the scope of conversational AI, the natural progression of exploration leads to the topic of what influence AI tools, and more specifically CAs, have had on the integrated marketing communications (IMC) of organisations. As a framework IMC has been evolving since the 1980s; its metamorphosis driven by both internal and external factors. The initial internal factor responsible for the creation of the IMC concept was the desire to simply coordinate the elements of the promotional mix – advertising, sales, promotion, public relations, social media and so on – to speak to the customer with “one voice” regardless of what that voice was saying to the customer (Kitchen et al., 2004). The very first definition offered by the Association of Advertising Agencies in 1991 defined IMC merely as “a concept of marketing communications planning” (Schultz, 1992, p.10). By 1997 Duncan and Moriarty (1997) recognised that IMC should not remain purely at the level of an individual marketing campaign and the juxtaposition of marketing communications channels; they elevated the concept to mean “a process of managing all sources of information about a product/service” (Duncan and Moriarty, 1997, p.3). This definition widens the scope of the IMC framework to encompass the entire marketing mix, rather than be limited just to communication. In the early 2000s the concept continued to evolve into an “audience-driven business process strategically managing stakeholders, content, channels, and results of brand communication programs” (Kliatchko, 2008, p.140), and “interactive and systematic process of cross-functional planning” (Porcu et al., 2012, p.326).

The outcomes and benefits of IMC depend on the level of maturity of the organisation and the level of integration adopted. Organisations that adopt IMC at a tactical or campaign level are only integrating their communications to potential customers, and not to all stakeholders; this type of integration is sporadic and inconsistent, and it produces communication that is transactional and is measured by the level of customer responses (Nowak and Phelps, 1994). On the other hand, organisations that have deeper integration that encompasses the entire marketing function and integrate communications not just to customers but also to other stakeholders, providing a framework for cross-functional coordination, are more likely to benefit from IMC by building customer relationships and increasing brand equity (Duncan and Moriarty, 1997). If organisations have highly developed support processes, such as excellent cross-functional coordination, appropriate management competences and top management support, then IMC outcomes and benefits become tangible at a strategic level where, in addition to brand equity, a positive impact can be witnessed for brand value, market share and profitability (Tafesse and Kitchen, 2017).

Considering these three broad levels of integration, AI has also brought different levels of benefit to organisations deploying conversational AI tools in their IMC. AI's role is multifaceted, bringing significant advantages to organisations by enabling engagement with customers to be more effective, efficient and personalised (Wen, Lin and Guo, 2022).

Customer insights and behaviour analysis are elevated to a higher level due to AI tools' capabilities to process vast amounts of customer data with unprecedented speed and accuracy. Every customer touchpoint, such as browsing a brand's website, engaging with social media or making a purchase, generates data points.

Where, previously, it was too expensive and time consuming to extrapolate patterns and insights from these data, which went largely unanalysed, AI tools now provide trends and insights that go beyond basic demographic information; AI tools provide deep analyses of customers on a holistic basis as well as predictions of future behaviour (Arasu, Seelan and Thamaraiselvan, 2020; Ma and Sun, 2020).

Personalised marketing and targeted advertising currently fulfil their potential only with the deployment of AI tools. Generic broadcasting of messages is no longer an effective way of communicating with customers whose expectations have evolved to prefer carefully curated and tailored offers reflecting their preferences, purchasing behaviours and needs (Chintalapati and Pandey, 2022). AI tools can achieve this level of personalisation through their ability to dissect and understand complex consumer behaviour patterns derived by algorithms that combine data from past purchases, search history, content interactions and social media activity; thus, AI tools create a unique image of each customer who can be targeted with a highly personalised message that resonates on a personal level with each individual (Alqurashi et al., 2023).

AI is also profoundly influencing the effectiveness and efficiency of content creation and curation by providing tools for marketers to produce fresh, relevant and engaging content with speed and accuracy. Natural language generation, a subset of AI, is the most critical tool that has augmented the role of the human marketing executive by producing coherent and well-written content that aligns not only with the brand’s voice and message, but also complements it with appropriate images, videos and graphics (Adwan, 2024). Curation of relevant content has also become a lot less labour intensive for marketers, as AI algorithms can sift through a vast array of web data to identify topical conversations relevant to the brand’s audience, aggregate the data and personalise it to specific audiences (Ahmed and Ganapathy, 2021; Patil et al., 2021).

IMC encompasses customer service communications, which have also been affected by AI through the introduction of chatbots and virtual assistants. Customers these days expect quick and personalised interactions, and chatbots are communication tools capable to provide exactly that by offering real-time, efficient and human-like conversations that allow brands to engage with customers across various digital platforms any time of the day (Cheng and Jiang, 2022). This capability provides a competitive advantage to brands in the face of the fast-paced digital environment and customers' expectations of an immediate response. Chatbots can provide relevant information, alert customers to new offers and keep customers engaged to foster deep customer relationships, which increase customer loyalty and thus actively contribute to the marketing strategy (Ho, 2021; Pantano and Pizzi, 2020).

Integrating AI in social media platforms and influencer marketing strategies is another aspect of IMC where AI tools enable brands to leverage data-driven insights, automate processes and enhance the effectiveness of campaigns. In social media, for example, AI can optimise the content delivery time by analysing large amounts of user data, such as patterns, preferences and purchasing behaviours, to ensure the message reaches the broadest audience possible (Capatina et al., 2020). In the area of influencer marketing AI provides analysis at the stage of identifying the most suitable influencers that a brand may wish to collaborate with by matching the audience demographics with the brand's target audience (Alboqami, 2023; Gerlich, Elsayed and Sokolovskiy, 2023).

2.3 Taxonomies of CAs

Researchers and practitioners provide a wide range of taxonomies of CAs of varying complexity and linked to a multitude of use cases. They vary in the number of dimensions considered and many overlap in their construction. One of the simplest taxonomies was proposed by Gnewuch, Morana and Maedche (2017); their taxonomy contained just two dimensions: primary mode of communication and context. This taxonomy differentiates between just two types of input a user can have access to – text-based (TB) or speech-based (SB) – and only two types of contexts – general purpose (GP) or specific domain (SD). The CAs using TB input are also known as “natural dialogue systems” and SB ones are referred to as “virtual” or “digital assistants”. These options create a simple two-by-two matrix for CAs to be classified in one of four types:

1) (TB) + (SD) – examples of this type can be found in museums (Vassos et al., 2016), healthcare (Zhu, Wang and Pu, 2022) or e-commerce (Noble et al., 2022).
2) (TB) + (GP) – examples include Cleverbot, created in 1997, which is one of the few remaining representatives of this group because recent technological advances have created the shift to SB versions of CAs (Schroeder et al., 2018).
3) (SB) + (SD) – one of the most successful mental health chatbots today is Woebot; Woebot allows users to start a conversation about well-being issues and it leads the conversation towards an outcome of advice on the next steps, which may include a referral to local health professionals (Fitzpatrick, Darcy and Vierhile, 2017).

4) (SB) + (GP) – current popular examples are available through Apple’s Siri and Google’s Home or can be accessed via a mobile app (e.g., Replika); they engage in general conversation on any topic to allow the bot to get to know the user better and adapt future responses (McStay, 2022).

Another simplistic two-parameter taxonomy was proposed by Følstad, Skjuve and Brandtzaeg (2018) that defined the dimensions of “locus of control” and “duration of relation”. This typology focused on the reciprocity usually observed in human communication and the relatively equal importance of each partner driving the conversation forward. Reciprocity is rarely observed in conversations with CAs where either the chatbot takes the lead and poses all the questions providing the human agent with only limited choices for their answer (chatbot-driven dialogue), or where the user has greater freedom how to phrase their request with perhaps free text or speech and the CA has to identify the user’s intentions and construct the adequate response. The second parameter takes into account the temporal characteristics of the interaction in which the dimension is short term at one end and long term at the other. Short-term interaction is typically a one-off conversation to solve a particular need. If the user visits the chatbot again, there will be no memory of previous interactions and the user will be treated as if they are a brand new customer. Chatbots from news agencies, such as CNN and *The Washington Post*, which curate news are examples of this type. For long-term engagement to be possible, the CAs would usually need access to the customer profile and memory of previous conversations to personalise the interaction and refine it each time the user returns. Examples of this type include the Woebot and Replika.

However, both of these classifications are rather too simplistic to capture the variables that differentiate modern CAs. A taxonomy with more than two dimensions is needed to describe the landscape of CA design frameworks. Feine et al. (2019) based a taxonomy of CAs on the “computers are social actors” paradigm and built on interpersonal communications theory; they classified CAs based on their abilities to interpret social cues. Their proposed taxonomy had four dimensions and 10 characteristics, including verbal, visual, auditory and invisible cues.

In the same year a study by Diedreich et al. (2019) built on the groundwork of Gnewuch, Morana and Maedche (2017) and posited that the capabilities of the underlying platform should be included when classifying CAs. It is these capabilities that will extend the functionality of the chatbots based on the preferences of the user and can include different types of analytics, hosting, training and integration. This taxonomy took the original two dimensions from Gnewuch, Morana and Maedche (2017) and through the application of Nickerson, Varshney and Muntermann’s (2013) method for taxonomy development added nine dimensions to the taxonomy. The nine dimensions are: *language* – single or multiple; *intelligence* – rule-based or self-learning (ML); *implementation* – programming, modelling, supervised learning or hybrid; *hosting* – on-premise, on the cloud or both; *pricing model* – usage-based, user-based, instance-based or free; *reporting* – without reporting or with reporting; *sentiment detection* – without sentiment or with sentiment; *enterprise integration* – none, application programming interface or pre-build interface(s); and *platform integration* – either single-platform or cross-platform.

Each parameter now contains two or more dimensions allowing the capture of more complex CAs that may have capabilities across the different dimensions. For example, the parameter of communication mode now allows for a category where both text and speech input are permitted, while the parameter of implementation captures the different approaches to building the dialogue flow within the CA –

whether through writing hard-wired code (programming), training the model with pre-labelled data (supervised learning) or a hybrid approach of combining two or more methods together. In practice, not all the characteristics of all dimensions are compatible with each other, and some are mutually exclusive; for example, it is not possible to design a good multilingual CA using the rule-based approach to intelligence. This notion of incompatibility supported by cluster analysis of the empirical evidence creates the basis for the definition of three archetypes that describe many of the CA platforms on the market. Archetype 1 shares the dimensions of being multilingual, self-learning and easily integrated with different enterprise systems. Representatives of this archetype tend to be the major technology players on the market such as Microsoft Azure, IBM Watson and Amazon Lex. CAs built on these platforms tend to use both text and speech as input modality, are trained on historical and current data that allows them to continue learning through ongoing conversations, and they are usually hosted in the cloud. We can see these capabilities in CAs aimed to assist business functions such as sales (Einstein from Salesforce), human resources and customer services (Amelia) (Kokshagina and Schneider, 2022). Archetype 2 represents CAs that are usually programmed for conversations on different topics, support only English language and mostly use modelling as the implementation approach. Representatives of this cluster are educational CAs such as Talkbot for Facebook (Smutny and Schreiberova, 2020) and platforms such as Landbot.io that provide customers with pre-populated templates on a variety of sales and marketing topics. Archetype 3 clusters the CAs that offer only text as an input option, are used for a specific task and are available through a single platform. A typical example of this cluster is

SurveyBot that offers interactive surveys through Facebook Messenger (Karumathil and Tripathi, 2022).

Building on the taxonomies of Gnewuch, Morana and Maedche (2017) and Diederich, Brendel and Kolbe (2019), in 2020 Janssen et al. (2020) and Jansen, Rodríguez Cardona and Breitner (2020) proposed two further taxonomies for virtual assistants in any context followed by another one specifically focusing on chatbots for B2B customer services. In Janssen et al. (2020) some of the dimensions and characteristics used have been adapted from previous research, such as intelligence framework (rule-based vs self-learning) and integration (stand-alone programme or systems integrated). However, they did propose new dimensions that were clustered into three perspectives: intelligence (knowledge structure features), interaction (technical features) and context (situational features). In the intelligence perspective the dimensions of personality processing and socio-emotional skills were added as key competences to be possessed by a CA if a user expects to have human-like communication, because conversational style needs to adapt to the context of the conversation and the user’s approach (Jain et al., 2018; Piccolo Mensio and Alani, 2018). A CA’s ability to recognise and adapt to the emotional states of the user is a key factor in increasing customer satisfaction and acceptance of the technology. In the interaction perspective, the dimensions of interface personification, additional human support, and number of participants were added to differentiate between embodied and disembodied CAs. Embodiment of CAs is the gateway to concepts such as anthropomorphism (Thomaz et al., 2020) and the new trend of designing avatars for the metaverse type of environments (Miao et al., 2022; Jones et al., 2022). The ability for a CA to know its limitations and know when the customer experience needs to be handed over to a human agent before the user experience suffers is a capability many CAs now possess having learned from the mistakes of the past (Zumstein and Hundertmark, 2017). In the context perspective the new dimensions of relation duration and motivation for use are the most interesting to explore, as the first one looks at the temporal characteristics of the human–computer interaction, which refers to a CA’s ability to remember and learn from previous conversations with the same user (Wei, Yu and Fong, 2018; Følstad, Skjuve and Brandtzaeg, 2018), and for the first time in any taxonomy the user’s motivations are taken into consideration and divided into productivity, entertainment, social and utility dimensions (Brandtzaeg et al., 2017).

Janssen, Rodríguez Cardona and Breitner’s (2020) second taxonomy focused more narrowly on customer services, specifically in the B2B sector. This taxonomy also proposed 17 dimensions; however, they differ from the ones in the previous taxonomy by focusing on the needs and expectations of business customers, including new dimensions such as industry classification, access to business data, data policy, action request and service request. Based on these dimensions, the typology proposed the three most common archetypes in this context: (1) the “lead generation chatbot” – task-oriented CAs designed to generate new business leads by encouraging users to leave their contact details for human follow up or to book a demonstration of the product. They would usually have predefined dialogue structure focusing on achieving a specific outcome without any distraction or small talk. (2) The “aftersales facilitator chatbot” is also a task-oriented CA with a design upgrade of offering a more personalised dialogue by collecting business information from users, such as number of employees, in order to recommend the appropriate course of action for the size of customer. (3) The “advertising FAQ chatbot” is a knowledge-based CA that is designed to search large databases of information and provide a recommendation to a user that is in response to a specific enquiry. It would seem from the data collected to create this typology that the majority of B2B CAs are aimed at the pre-purchase stage of the sales funnel (Archetype 1 and 3), which is the domain of the marketing function; many parallels can be observed between B2B and B2C domains when it comes to collecting customer data for further contact and providing information to stimulate the purchase intention.

Nißen et al. (2022) suggested by far the most comprehensive and complex taxonomy of CAs to date; they proposed grouping the perspectives in three layers: the chatbot, the chatbot + user and the user. These layers are then divided into five perspectives: two of the perspectives, temporal profile and appearance, are new perspectives, which were added to the three perspectives of intelligence, interaction and context proposed by Janssen et al. (2020).

The temporal profile perspective and dimensions measure how long the entire interaction lasts from start to finish with one end of the spectrum being a single or few interactions and the other end being multiple interactions over a prolonged period of time. The vast majority of CAs (84%) are developed with a short-term horizon in mind (Janssen et al., 2020); this is particularly the case in marketing and e-commerce applications where the goal of the interaction is to move the customer to the next stage of the consumer journey as efficiently and effectively as possible. These CAs are also more likely to have conversations that are unrelated to previous interactions, whereas ones with longer term temporal design would usually be able to pick up from where the conversation ended the previous time. A lack of continuity creates the impression that these CAs are less sophisticated and they are therefore usually deployed as human assistants rather than as replacements for a particular communication channel (Nißen et al., 2022).

From the various dimensions of the intelligence perspective, perhaps the most influential on the choices of all others is the choice of framework that is used as a basis for choosing the remaining of the CA's functionality, appearance and interaction dimensions (Diedrich et al., 2019; Janssen et al., 2020; Nißen et al., 2022). This classification of dimensions is very much inward looking in that it defines the inner workings of a CA onto which the outer looking interaction dimensions are based. The dimension of socio-emotional behaviour, for example, refers to the level of human-mimicking behaviours that may be part of the programming, such as using emotionally charged words, display responses that can be considered empathetic or even quirks of speech such as “hm… let me think about this” (Riva and Marchetti, 2022). Marketing CAs of international institutions also tend to speak to their customers in the local languages of the countries they serve; therefore, multilingual models are now often developed to accommodate the preferences of the customers and put them at ease by communicating in their native languages (Danielescu and Christian, 2018).

The dimensions in the context perspective are primarily driven by the motivations that users have to interact with the CAs. The success of that interaction mainly depends on the match between the CA's design and the customer's goals (Nißen et al., 2022). In the context of HE, CAs have been traditionally developed to support students in their learning journey by providing academic support (Li, Xiang and Leite, 2022; Ceha and Law, 2022), soft skills (Dell'Aquila et al., 2022), coaching (Winkler and Söllner, 2018) or well-being support (Yang and Evans, 2019; Agarwal and Linh, 2021).

From Nickerson et al. (2013) to Nißen et al. (2022), it has been recognised by many of the creators of taxonomies that it is important to keep taxonomies updated as the capabilities and domain applications of CAs evolve over time. In the available taxonomies, the evidence is based on a wide range of industries and use cases for CAs. Some included the education domain in their empirical research (Janssen et al., 2020; Nißen et al., 2022; Motger, Franch and Marco, 2022). Motger, Franch and Marco (2022) in particular, examined in greater depth the typology of CAs used specifically in the education domain; they classified the chatbots into two types: CAs for e-learning and career support. There is, however, a much wider use of CAs in education, and the gap that is evident is the lack of research in the use of CAs across the entire student journey – from chatbots designed to support students at the start of their consumer journey while they are still deciding on the right course for them, all the way to the end when they become alumni.

Other taxonomies exist that were developed in the context of very narrow application fields, such as healthcare or clinical settings. Analysing these taxonomies, it is clear that their application in other fields and industries is limited. For example, both Laranjo et al. (2018) and Montenegro, da Costa and da Rosa Righi (2019) listed familiar dimensions, such as task orientation and dialogue initiative, but added very healthcare-specific new ones, such as health domain areas (e.g., nutrition, neurology, dermatology, etc.) or health goals (e.g., prevention, diagnosis, elderly assistance, etc.). (See Appendix 1 – taxonomies of CAs.)

2.4 Conceptualisation of the Student Journey in HEIs

In this section, the links between the concepts of “student journey”, “student recruitment” and “consumer journey” are explored and compared. A “holistic student journey” model is proposed to support the aims and objectives of this study.

2.4.1 Student Journey

In existing studies, the “student journey” is conceptualised as students’ experiences starting with induction into their degree programmes, continuing during their time of study and finishing with the time they graduate (Weaver, 2013; Osborne, Loveder and Knight, 2019; Munguia and Brennan, 2020). Many studies explore aspects provided by support technology during the time students actively engage with their programmes. For example, Munguia and Brennan (2020) examined the role student learning analytics plays in improving the progression of students from one module to the next within the programmes they study. Learning analytics plays an important role in identifying weak points in the programmes where students may withdraw or pause their studies and where an intervention may be needed to improve the course structure. Similarly, Gray, Perkins and Ritsos (2020) demonstrated that visualising the results of learning analytics tools, which they called “degree pictures”, can aid students and support staff in better understanding the challenges that need addressing and pinpoint the appropriate moments for academic or pastoral interventions. Humphrey and Lowe (2017) were concerned with how cutting-edge technology alongside modern teaching rooms can help students increase their “sense of belonging” and enhance their engagement while studying their degree programmes. Weaver (2013) focused on how technology changes and supports library services by embracing rich media in diverse ways to reach and retain students through engaging them online.

When analysing the academic literature specifically for aspects of using CAs in education, research proliferates in areas such as learning processes, student support and well-being to name a few. For example, Winkler and Söllner (2018) examined the problem of large lecture groups where it is becoming increasingly difficult for lecturers to provide individual and personalised support to their students, which leads to low levels of achievement and attainment. One proposed method to tackle this issue is the deployment of “pedagogical agents” in the form of chatbots that can provide students with immediate and customised instruction and feedback (Kim, Baylor and Shen, 2007). The challenges of increasing class sizes were also the focus of Cunningham-Nelson et al. (2019); they posited that students value highly being treated as individuals and this is an important contributing factor for enhanced academic performance and satisfaction. Again, chatbots were proposed as a means to meet this goal by providing in the first instance standardised information, such as location of resources, due dates and assessment information.

Pérez et al. (2020) made the distinction that chatbots in education perform one of two distinct roles: “service assistants” or “education agents”. The first type is similar to chatbots used in many other industries, such as medicine, banking or customer service, and simply aims to answer frequently asked questions or to direct students to the appropriate information or services, especially during peak times like induction. The second type’s main purpose is to relieve pressure and reduce the workload of human instructors by aiding in the revision and feedback tasks in a specific subject for specific students who may need additional help due to language or accessibility issues.

Hwang and Chang (2021) pointed out that the majority of existing research on the effectiveness of chatbots in education is conducted through quantitative research and thus does not analyse in depth the pedagogical benefits of incorporating them in the learning process or their impact on student outcomes. It is argued that the benefits of chatbots in education can be easily seen in cases of improved real-time interaction (Kim, Cha and Kim, 2019) or improving learning efficiency (Wu et al., 2020) and even peer communication skills (Hill, Ford and Farreras, 2015); however, very few studies have explored the benefits chatbots can bring to curriculum design, overall learning strategies or their effects on students' learning behaviours. No evidence of research was found that evaluates the use of chatbots in areas such as peer assessment, issue-based learning, project-based learning or enquiry-based learning; these types of tasks generally require higher order thinking.

2.4.2 Student Recruitment

The stage prior to starting a degree programme is examined separately from the student journey in the literature and is conceptualised as "student recruitment" (Frølich and Stensaker, 2010; Becker and Kolster, 2012; Ortagus and Tanner, 2019). Here, once again, the role of technology plays a central role in many studies on the subject. Zhao et al. (2021) focused on the use of VR in the recruitment of undergraduate (UG) students; in some HEIs, students are invited to have a virtual tour of the campus and teaching facilities, and they can access further information about courses through interactive software. Some VR experiences also have gamification features that invite students to chase and capture cubes with further information and prizes. Ortagus and Tanner (2019) specifically examined the factors that lead to successful student recruitment for online degree programmes. In this context, institutions that prioritise personalisation of the interactions between the degree provider and the prospective students during the recruitment process are considered to be more successful. Bock, Poole and Joseph (2014) asked whether university branding may be influencing the success of student recruitment and concluded that the “latest technology” is one of the top 10 factors ranked as attractive by prospective students. When exploring international student recruitment through the lens of social media, Vrontis et al. (2018) proposed a model for education institutions in which social platforms were a fundamental part of their marketing communication plans and student recruitment strategies.

When searching for academic research specifically on the use of chatbots in student recruitment activities, there is very little literature available in both qualitative-led and quantitative-led studies. The few papers on the subject explored the topic from either a technical perspective or as part of an orientation and retention campaign. For example, Sudiatmika and Ariantini (2021) discussed the choices made when designing a platform and building the knowledge base of a chatbot to act as question-answering tool for prospective students on the topics of cost, programme information, programme profile information, and the registration process. The structure of the conversation flow and the possible answers given to any given enquiry were pre-programmed and inflexible, which suggests that the chatbot was built following a rule-based framework. Similarly, Alkhoori, Kuhail and Alkhoori (2020) also built a chatbot based on frequently asked questions from potential students using the DialogueFlow platform from Google and code answers relating to course information, enrolment, scheduling, academic and career goals, and other general enquiries. They differentiated between expert systems and chatbots on the basis that both aim to assist the student in selecting the right course, but the former is based on a form and quite difficult for students to complete if they do not understand all the choices, whereas the latter is conversation based allowing the student to ask clarification questions using voice or free text.

On the other side of the recruitment process, Elnozahy et al. (2019) explored a chatbot that assists a university admission team in its assessment of which students to offer a place in their institution; a prospective student's answers to a series of questions presented as a game are evaluated and combined with other internal and external data to predict the student's retention and success prospects. The game is calibrated to measure the relevant skills and competencies for each education programme and depending on the results students are advised to choose one or another major.

2.5 Customer Journey Mapping

This research aims to explore the concepts of "student journey" and "student recruitment" that mirror the wider concept of the "customer journey" in marketing. The process of consumer journey mapping has been of research interest since the end of the nineteenth century with the publication of the very first customer journey map by the American advertising advocate Elias St. Elmo Lewis (1898). More recent studies have attempted to define the "customer journey" or the "customer decision journey" (used interchangeably) taking into consideration recent economic, technological and social phenomena that are influencing research and practice (Santos and Gonçalves, 2021). Since the early 2000s, the consumer journey is described using concepts such as it being a "process", achieving a "purchase", having an "experience" and feeling "satisfaction". Understanding the process of consumer journey mapping starts with understanding the consumer decision-making process which, according to Erasmus, Boshoff and Rousseau (2001), is a behavioural pattern that precedes, determines and follows a decision process comprising multiple stages in order to satisfy a product need or reach a choice. The concept that the customer journey is a “process” leading to an outcome is the core concept proposed by Vázquez et al. (2014, p.70) who proposed a “marketing model that illustrates the purchase process in several stages, from the moment when a customer is aware of the existence of the product (awareness) to the moment when he or she buys the product (purchase). This definition was supported by Følstad and Kvale (2018, p.207) with their interpretation of the customer journey as “the sequence, process, or path through which customers access or effectively use a service”. Lemon and Verhoef (2016) added to the definition by stating that all the steps of the process should add up to customer satisfaction. Shavitt and Barnes (2020, p.40) took the definition to another level by proposing that “the consumer journey is the steps consumers take in their path towards building relationships with brands or experiences that are satisfying”.

The field of consumer journey mapping started with Lewis’s 1898 AID (Attention, Interest, Desire) model, which he further developed two years later into the seminal AIDA (Attention, Interest, Desire, Action) model (Lewis, 1900) that is still widely used today (Rishi and Popli, 2021; Song and Kim, 2021; Softić et al., 2021; Vollrath and Villegas, 2022). Consumer journey models can be divided into two broad categories: models that break down the customer journey only up to the point of purchase, and models that extend the journey beyond that point. From 1900 until 1978 all but one model finished with the “Action” stage. Examples include Hall’s (1915) AICCA model (Attention, Interest, Confidence, Conviction, Action); Ramsay’s (1921) AIDCA model (Attention, Interest, Desire, Caution, Action);; Devoe’s (1956) AIDMA (Attention, Interest, Desire, Memory, Action); Wolfe, Brown and Thompson’s (1962) AAPIS model (Awareness, Acceptance, Preference, Intention, Sale); and Robertson's (1971) ACALTA model (Awareness, Comprehension, Attitude, Legitimation, Trial, Adoption). Sheldon (1911) proposed the AIDAS (Attention, Interest, Desire, Action, Satisfaction) model, which was the first model to account for a stage beyond the point of purchase. From the late 1970s we see the post-purchase stage regularly included in customer journey models. Examples include McGuire's (1978) PACYRB model (Presentation, Attention, Comprehension, Yielding, Retention, Behaviour); Puccinelli et al.'s (2009) NIEPP model (Need Recognition, Information Search, Evaluation, Purchase, Post-Purchase); Lemon and Verhoef's (2016) PPP model (Pre-Purchase, Purchase, Post-Purchase); Colicev et al.'s (2018) APS model (Awareness, Purchase Intent, Satisfaction); and Demmers, Weltevreden and van Dolen's (2020) PCP model (Pre-consumption, Consumption, Post-consumption). A comparison table of the most prominent models is available in Appendix 2.

Comparing these models from the past 120 years, there is a clear similarity of thinking that seems to have permeated throughout the decades and provided a substantial contribution towards our understanding of the consumer journey. They also reveal some shortcomings that need to be taken into consideration when applying these models in the current social, technological and marketing environment. According to Egan (2015) and Wijaya (2015) there are three limitations to consider:

1) Linear models, as the ones described above, do not take into consideration potential interactions between the stages. Current thinking proposes models of consumer decision journeys that are non-linear, more circular and interconnected (Egan, 2015).

2) Historical models do not sufficiently incorporate the effects of new IT and associated communication channels such as social media. Research has shown that online channels have changed the way people communicate with brands and with each other, how they socialise and how they influence the behaviours of others (Wijaya, 2015; Colitsev et al., 2018).
3) The proposed models infrequently consider post-purchase experience as a valid stage in the consumer journey. Satisfaction, sharing and liking/disliking are now recognised as an essential part of consumers' experience with brands (Batra and Keller, 2016; Wedel, Bigné and Zhang, 2020).

More recently, academic research has investigated the impact of CAs and other AI tools on the consumer journey. Lee and Lee (2020) explored the shape of an "untact" customer journey where, enabled by smart digital technologies, customers complete their journey without any contact with human service agents. Wolbers and Walter (2021) measured the trust and convenience provided by intelligent voice assistants and their impact on the different stages of a brand's consumer decision journey. They argued that the value voice assistants bring is to shorten and simplify the decision journey, particularly when in relation to returning customers and repeat purchases. Saura (2021) took the view that one of the benefits of the new AI tools in marketing is that they enable organisations to mine their customer data in such a way that they can provide personalised interactions that lead to an increase in customer satisfaction.

Hoyer et al. (2020) took a holistic view of assessing the influence of new AI technologies, including CAs, on the pre-transaction, transaction and post-transaction stages of a shoppers' journey along the brand experience dimensions proposed by Schmitt (1999) of sense, feel, think, act, relate. Their study proposed that CAs in the pre-transaction stage perform the tasks of selecting relevant information, advising, and customising the choice set for a particular customer. The success of these actions is greatly dependent on the customer's prior browsing and purchase history as well as "collaborative filtering", which aggregates data from the purchases of other customers (Yoon et al., 2013). Hoyer et al. (2020) also proposed that the highest impact CAs will have along the customer journey will be in the pre-transaction stage, compared to the transaction and post-transaction stages, where technology can improve customers' product knowledge by providing information, customising recommendations, advising on choices and thus increase customers' curiosity, enjoyment and fun.

In their research, Nam and Kannan (2020) postulated that even though interactive and smart technologies are available globally, the way customers interact with them differs depending on their location, culture and market conditions. Customers' preference and use of technology-driven touchpoints would differ in different market economies and thus organisations have the opportunity to gather data through devices, such as virtual agents, to customise their marketing strategies and campaigns for the best result in customer acquisition and retention.

Tueanrat, Papagiannidis and Alamanos (2021) identified five underlying themes relating to the current state of knowledge on the customer journey and one of them is the effect of technological disruption. They claimed that new smart technologies not only augment the traditional customer decision-making process but, in some cases, replace it altogether by eliminating the need to make a choice or decision in the first place. This makes the customer a part of the process and the current customer journey less hierarchical and more fluid. The example given by De Bellis and Johar (2020) is a situation where virtual assistants act as "personal digital concierges" that interpret and anticipate our shopping needs and even make the decisions of which item to buy, how much and when by automatically ordering items that need replenishing.

When comparing the two concepts of “student journey” and “student recruitment” with the marketing view of a whole “customer journey”, we can see an apparent disjointedness in how students’ experiences are separated and not examined as one holistic and coherent “journey”. Drawing on the models presented by Wijaya (2015), Lemon and Verhoef (2016), Colitsev et al. (2018) and Demmers, Weltevreden and van Dolen (2020), this study proposes a new conceptualisation of the “student journey” modelled on modern consumer journey research; the proposed conceptualisation combines the pre-commencement and post-commencement stages of study in one comprehensive model. This model (Figure 2.3) proposes a view of the student journey that extends the view given in traditional models in the literature in that it does not begin with the first day a student comes to campus to begin their studies or logs into their learning environment. Instead, the first moment a student is “aware” of their desire to undertake a university course and begins the process of searching for relevant information about courses, universities and potential careers that follow is considered the start of the journey. The journey then continues with “evaluation” of the choices, which will include activities such as researching using various sources and platforms, shortlisting the most attractive offers and compiling a consideration set. The stages of “application” would follow where students actively engage with their shortlisted courses; this stage concludes with the recruitment stage and “enrolment” in the final choice. This is where the student would continue in the second stage of purchase (Lemon and Verhoef, 2016), which in the case of HE can last several years, depending on the programme of "study", and culminate in the post-purchase stage when students become "alumni" but are inextricably linked to their organisations of study for many years after that.

This model provides a comprehensive foundation for this study by allowing for the stages of the student journey to be linked in a holistic way and it provides insights into the potential long-term effects of incorporating CAs early in the student journey.

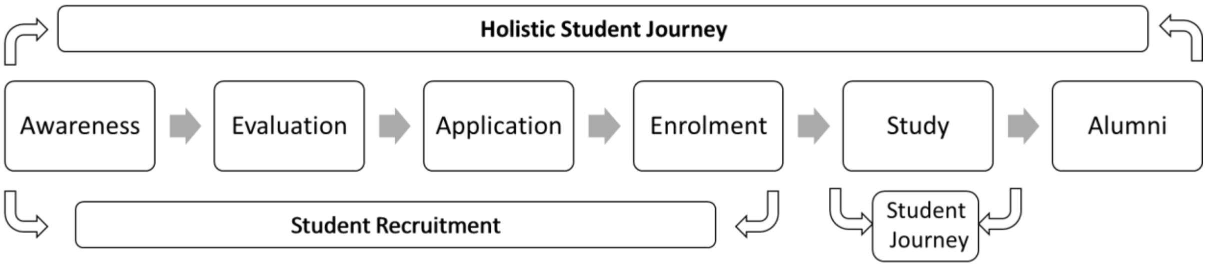

Figure 2.3. Holistic Student Journey Model (Source: Author, 2024)

2.6 Theoretical Frameworks

Among the many theories that seek to explain human behaviour in interactions with technology, this study will concentrate on two key ones chosen for their numerous touchpoints and overlapping elements: the ELM (Petty and Cacioppo, 1986) and the UTAUT2 (Venkatesh, Thong and Xu, 2012).

ELM is a dual-process theory providing a "general framework for organizing, categorizing, and understanding the basic processes underlying the effectiveness of persuasive communications" (Petty and Cacioppo, 1986, p.125). Even though this model was conceived in the mid-1980s, when AI tools were far less sophisticated and not widely used in marketing communications, it is still found to be relevant and useful today; for example, ELM was used to underpin research in online communication in the context of travel websites and interactive technology adoption as demonstrated in Camilleri and Kozak (2022), and ELM was used in Palla, Kyriacou and Zarkada's (2022) study on the effect of product involvement on attitude formation and strength in the digital channels, specifically in the context of e-commerce.

ELM proposes a framework that attempts to explain how attitudes are formed and changed based on the strength of people's motivation and ability to apply cognitive effort in processing persuasive information. According to this framework, there are two routes to achieve the final goal of attitude change. The central route is activated in situations where an individual applies thoughtful and thorough analysis to the message, carefully considering facts, features and product details, which enables them to form an enduring positive or negative attitude change (Petty and Cacioppo, 1986). This process is also known as the cognitive-based process, because it requires more cognitive resources and is described as effortful, reflective and deliberate (Breves, 2021). Through this process, customers "elaborately process information", thus following central and systematic clues that create a high level of involvement with the message being communicated (Fan, Gao and Han, 2023, p.3). In the context of this study, ELM has been adopted and popularised by the advertising and marketing industry to evaluate attitudinal change following persuasive messages when customers need to make a considered purchase, such as choosing the right university course that will allow them a path into their desired profession or industry (Kitchen et al., 2014).

The second route to attitudinal change is the peripheral route, which is usually activated by a simple cue in the persuasion context that causes a change in the receiver's perception without this being its primary objective or without the necessity of the receiver having to evaluate the true merit of the information presented (Petty and Cacioppo, 1986). This affective-based process is more automatic; it relies on the use of heuristic cues rather than strenuous cognitive activities and is used by customers with low levels of both motivation and ability to engage in the alternative central or cognitive route (Breves, 2021). Customers are said to have low involvement in the purchase and they make their decisions based on peripheral factors, such as appearance and voice, and environmental cues, such as digital platforms used (Fan, Gao and Han, 2023). Punj and Moore (2009) focused on the peripheral route in an attempt to explain how customers' information search and formation of a consideration set are influenced by the web environment in which customers make their choices. They specifically looked at the number of choices and amount of time available to customers and how that influences their attitudes towards purchasing from online stores. Leong et al. (2019) also based their research on ELM in the context of hotel bookings and specifically how electronic word of mouth might be influencing customers' perceptions, behaviours and adoption of internet-based technologies.

While the two routes may seem mutually exclusive, in fact, it is often observed that the two information processing modes can operate in parallel with each other, which suggests that customers may operate on the basis of both cognitive and emotional cues (Kang, 2016). This is particularly relevant for occasions when customers interact with CAs, where the information provided could be perceived via the central route if the decision relates to a high involvement purchase, but also via the peripheral route that takes into account the chatbot's choice of personality, voice and appearance if paired with an avatar. Therefore, this dual-process model appears to be very suitable for the exploration of how CAs might influence the decision-making process of prospective students in HEIs.

Undoubtedly, this model has maintained its popularity over the years since its conception; it is widely applied in advertising and marketing (Shumann et al., 2012) to explain attitudinal changes based on the strength and appropriateness of marketing messages. The model is well constructed, clearly and simply explaining the persuasion process, and is very descriptive and versatile, which allows it to encompass various situations and outcomes (Kitchen et al., 2014). However, doubts have also been raised about its practical application when applying the model to try to predict outcomes from a particular marketing campaign, rather than just analyse historical data (Szczepanski, 2006), or when applying it in more personalised contexts that modern AI tools create, which were not present in the mid-1980s when the model was conceived in the era of mass marketing (Kitchener, 2013).

UTAUT2 is an alternative framework that seeks to explain humans' behaviour when interacting with technology, and specifically the extent to which customers would accept and use the technology as a medium of communication with brands. Developed by Venkatesh, Thong and Xu (2012), UTAUT2 traces its origins back to the 1980s when Davis (1987) formulated the original TAM. Other scholars developed TAM over the years to arrive at a more comprehensive set of parameters that attempt to explain why some technologies are better accepted than others. The original two factors proposed by Davis (1987) were extended by David and Venkatesh in 2000 when they developed TAM2, which included additional theoretical constructs representing social influences, such as subjective norms, voluntariness and image, as well as cognitive factors, such as job relevance, output quality and result demonstrability. The first iteration of UTAUT was proposed by Venkatesh et al. (2003) where the focus became not just any technology, but specifically information technology (IT). They proposed four constructs as primary factors influencing acceptance and use: performance expectancy, effort expectancy, social influence and facilitating conditions. What UTAUT2 (Venkatesh, Thong and Xu, 2012) brings to the table is the adaptation of these constructs specifically to the context of consumer technology acceptance, which is most relevant to the goals of this research study. In this context, performance expectancy refers to the level of benefit customers will obtain by performing certain tasks using this technology; effort expectancy is linked to how easy customers will find it to use the technology; social influence seeks to explain how important the opinions of close relatives and friends are when using this technology; and facilitating conditions refers to the resources and support available to perform certain tasks on the chosen technology. Not only are the original four constructs redefined for this specific context, but the authors of UTAUT2 also added three additional constructs, namely hedonic motivation, price value and habit. The authors recognised that utilitarian value, or extrinsic motivation, was already captured by the performance expectancy construct, which is a strong predictor of behavioural change, and they added the intrinsic or hedonic motivational factor (i.e., the fun and pleasure experienced when using the technology) to complement the model (Vallerand, 1997). Price value is one of the main constructs that differentiates UTAUT from UTAUT2 as the former was devised for organisational settings where employees do not bear the cost of obtaining the technology, while the latter was devised from a consumer use perspective where they do. Price, apart from having monetary value, is also an indicator of quality when it comes to comparison between brands and a sign of perceived quality of the technology. Therefore, price value in this context can be conceptualised as a trade-off between cost and benefit (Venkatesh, Thong and Xu, 2012). Lastly, habit was introduced to counter criticisms of the previous iteration of the model because not all human behaviour is intentional and pre-planned, sometimes it is automatic and subconscious. Habit as a construct was defined as “the extent to which people tend to perform behaviours automatically because of learning” (Limayem, Hirt and Cheung, 2007, p.705). The extent of habit formation is greatly dependent on the frequency and duration of technology exposure and use; thus, the underlying habit may have a spectrum of strength and importance for different individuals (Venkatesh, Thong and Xu, 2012).

The final change Venkatesh, Thong and Xu (2012) introduced in order to tailor the UTAUT model to the consumer technology use context is that in the UTAUT2 model three facilitating conditions of age, gender and experience are added. They act as “perceived behavioural controls” (Ajzen, 1991) and influence both customer intentions and their actual behaviours. For example, taking age as a moderating factor, older consumers may face more difficulties in processing new or complex information, thus affecting their motivation and ability to adopt new technologies (Morris, Venkatesh and Ackerman, 2005). The factor of experience taken in the context of technology suggests that customers with a greater degree of experience would usually have greater familiarity and knowledge, which facilitates learning and increases independence (Venkatesh, Thong and Xu, 2012).

More recently, Venkatesh (2022) adapted the UTAUT framework specifically for the context of AI tools used in operations management. On the one side, the barriers to adoption explored are related to the AI tool itself: (1) black box models (lack of transparency in the underlying algorithm); (2) errors – caused by sparce data combined with dynamic changes in the environment; (3) time – for a model to be effective it needs time to learn and be improved; (4) bias – the underlying training data is often riddled with human bias which is amplified by the AI tool. On the other side, the barriers to adoption relate to the organisation and its employees: (1) human biases – humans are unique and each individual has their own biases and heuristics which often lead to mistakes and irrational opinions; (2) algorithm aversion – distrust in the judgements of algorithms, humans tend to trust the judgement of another human more than the judgement of a machine; (3) lack of organisational infrastructure – integrating AI tools in the organisation require resources, staff training and time; (4) changing environment – there are multiple stakeholders due to the size of the organisation and the external environment is constantly in flux. On the positive side, AI tools are welcomed into the workplace due to their ability to process large volumes of data in real time, and to produce analysis, predictions and recommendations that are a useful tool in an employee’s decision making, which allows for more strategic and abstract thinking.

Equally, the UTAUT2 model has also been applied in research of AI tools in the context of different industries and use cases. For example, Gansser and Reich (2021) proposed five additional influencing variables to the model when applied to the context of smart homes: health, convenience and comfort, sustainability, safety and security, and personal innovativeness in the IT area. In the education field, Rudhumbu (2021) applied the UTAUT2 model in the context of university students’ blended learning to predict which factors may impact their acceptance and use. They found that while habit and price value were not great predictors, the remaining factors had positively influenced their intentions and actual behaviour. Similarly, the UTAUT2 model was used to explain the adoption of AR use in university settings

(Benrahal et al., 2022) and the use of chatbots for learning the Chinese language (Chen, Widarso and Sutrisno, 2020). In the field of smart products, McCloskey and Bennett (2020) applied the UTAUT2 model to the question of adoption of smart speakers. They empirically asserted that only three of the seven factors, which were performance expectancy, price value and habit, had a positive influence on acceptance; the other four factors did not make a statistically significant difference to the intention or behaviour or customers. Similarly, Chu et al. (2022) extended UTAUT2 with additional modifying factors, such as environmental consciousness, AI optimism attitude and perceived quality, when applying the model in the context of smart elevators. In health management, Huang and Yang (2020) turned their attention to consumers' intentions to use an artificially intelligent mobile application for the purpose of weight loss and general health outcomes.

Both ELM and UTAUT2 were developed independently and for different purposes. However, links and overlaps are evident in the factors of both models. The first apparent link is that both theories recognise the importance of human motivation as a conditioning factor for engagement with the message or the technology. ELM argues that high motivation paired with high ability will direct customers towards the central route of information analysis, while low motivation and ability will direct customers towards the peripheral route. UTAUT2 differentiates between intrinsic motivation (hedonic motivation) and extrinsic motivation (performance expectancy) and puts both on the same level as two of the seven factors in the model. The second link is seen in the sphere of social influence. ELM suggests that the peripheral route relies heavily on social cues, such as source of information, which can influence the attitudes and behaviour of customers, while UTAUT2 has added social influence as a stand-alone factor when developing the model from its previous iteration. Thirdly, personal and organisational abilities are embedded in the factors of both models. ELM suggests that the central route of information processing is likely to result in long-term attitudinal change only if the individual has a high ability to do so, while UTAUT2 posits that the factor of facilitating conditions is the equivalent construct of personal and organisational resources that permit individuals to adopt a technology. These links are illustrated in Figure 4.

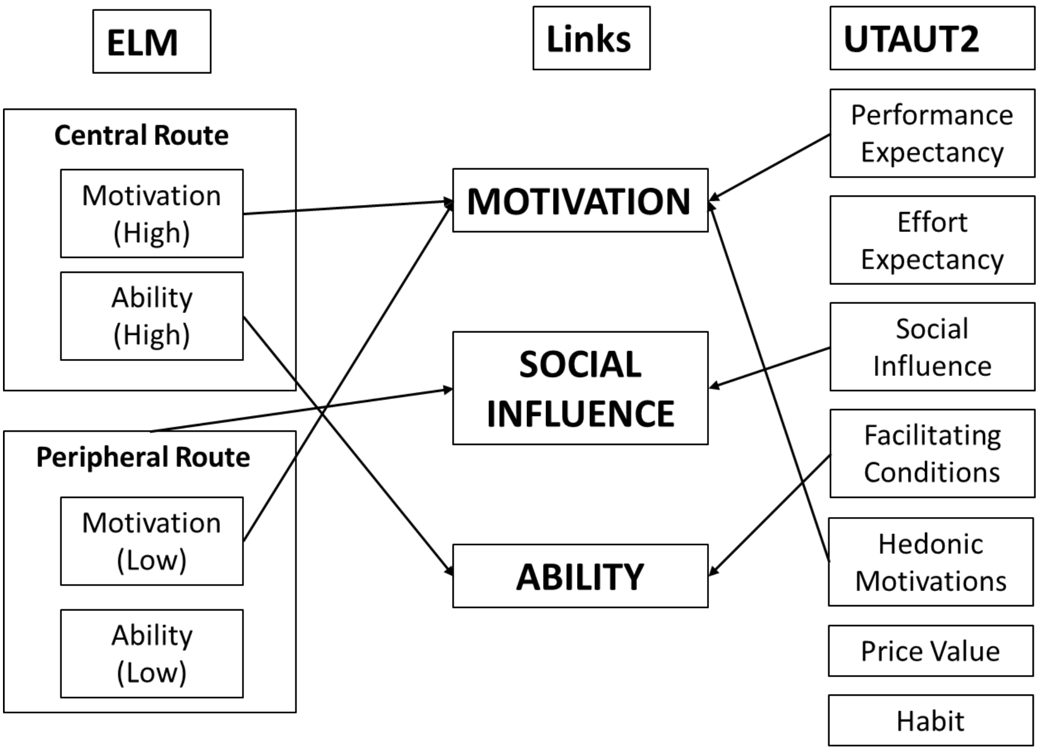

Figure 2.4. Links between ELM and UTAUT2 (Source: Author, 2024)

2.7 Summary

This chapter developed a critical review of the literature relating to AI in general, the narrower field of conversational AI and the topics of student journey and student recruitment. It summarised past developments and traced the evolution of the concepts up to the present day supported by examples of the application of the various concepts in the context of different industries. Taxonomies of CAs were compared and contrasted. Customer journey mapping was explored and applied in the creation of a “holistic student journey” concept that underpins this research. Finally, two theories – ELM and UTAUT2 – were chosen, analysed and compared with each other in the search for commonalities and overlaps.

The next chapter will detail the research design of this dissertation.

CHAPTER THREE
RESEARCH DESIGN

3.1 Introduction

The previous chapter critically evaluated the extant literature and provided justification for the theories chosen to underpin this research study. It provided understanding of how the concepts of AI, conversational AI and CAs relate to one another as well as their significance in the role of marketing strategies. Furthermore, it proposed a new holistic viewpoint of the student journey.

The aim of this chapter is to present and justify the methodology employed in pursuing the objectives of this study. Firstly, it examines the paradigmatic underpinnings guiding the methodological approach. Secondly, the chapter provides a defence for the use of a qualitative methodology and its suitability for this topic of enquiry. The social constructivism methodology is introduced and linked to the aim and objectives of the study. The chapter continues with justification for sample selection and size and data collection methods. Axiological and ethical considerations are explored alongside reflections on the criteria of research quality and validity (Maxwell, 2013; Guba and Lincoln, 1994; Denzin and Lincoln, 2011).

3.2 Research Paradigm

The adoption of the appropriate research paradigm is a key factor that shapes the academic value and knowledge outcomes of this research. The concept of “paradigm” that forms the basis of this discussion is drawn from Kuhn’s (1970, p.175) original definition that has formed the basis of paradigmatic discussions in science ever since: “the entire constellation of beliefs, values and techniques, and so on shared by the members of a given community". Despite the broad nature of this definition, paradigms in contemporary research tend to focus on broad philosophical beliefs such as positivism, realism, pragmatism, postmodernism and interpretivism, where each one dictates the more specific methodological strategies that best serve that philosophical stance (Maxwell, 2013).

The positivist paradigm, often preferred in relation to the technical side of AI research, is grounded in the epistemological view that truth is objective; it is grounded in the belief that phenomena can be observed and measured, and empirical evidence can be produced that can be tested and replicated (Clark et al., 2021). As the central notion of objectivity argues that the researcher should remain detached from the subjects of the study to prevent bias and ensure reliability (Creswell, 2014), the obvious choice of methodology should be a quantitative survey, to test a pre-established hypothesis and seek to discover a cause-and-effect relationship using standard statistical methods. In addition, on an ontological level, the positivist stance is that reality exists independently of human perceptions; hence, the laws that govern human behaviour can be uncovered through systematic observation (Guba and Lincoln, 1994).

These rigid assertions of the positivist paradigm can lead a researcher down a path where the data collected are stripped of all their contextual richness. A positivist approach can simplify the complexity of social phenomena and fragment the meaning of words and expressions provided by participants; thus, it removes key components of the setting and circumstances in which words should be interpreted. This reductionist approach is quite misaligned with the objectives of this research, which require a level of flexibility and openness to understand the nuances of human attitudes, beliefs and values, especially in the context of a new and unfamiliar technology, which may not yet have a well-established cause-and-effect relationship to be discovered.

Pragmatism is an alternative paradigm often selected for AI-related research papers; it is deployed with the purpose of solving a specific real-world problem and often combines quantitative and qualitative approaches, which makes it suitable for mixed methods research (Creswell and Plano Clark, 2023). Epistemologically, pragmatism emphasises the value of knowledge, which is determined by the utilitarian value various solutions bring to a problem, rather than a deep understanding of the nature of knowledge itself and the subjective meanings individuals assign to their experiences (Biesta, 2021). Ontologically, the focus of pragmatism omits an exploration of subjective realities in favour of practical outcomes regardless of the meanings of these outcomes to the people affected (Morgan, 2014). While pragmatism can provide valuable insights relating to the objectives of this research and can identify what solution may be practical or effective, it would simultaneously limit the research to what is meaningfully understood and not seek to capture rich, context-specific insights into how individuals perceive and make sense of their experiences. The research objectives lean firmly to the interpretivist side of the paradigmatic spectrum, which is explored further in this chapter.

As the adoption of conversational AI in different industries is still nascent, the research opportunities from a paradigm perspective are still quite wide as there are still many gaps in knowledge and new gaps are created as the technology evolves rapidly, even on annual basis. Recent and current research tends to follow one of two approaches in exploring the topics of AI: the positivist approach or the pragmatic or interpretivist approach. The positivist approach is often adopted by the computer science and IT community. Research from these university departments tends to get published in leading computer science journals and conferences with a very technical orientation, such as the Association for the Advancement of Artificial Intelligence and International Conference on Machine Learning. The pragmatic or interpretivist approach is often adopted by academic researchers who attempt to connect the advances in this technology with its application in business and industry, the management of organisations, and organisational and behavioural theories. These studies allow for the exploration of more complex interplays of AI with the business environment and its impact on people and their jobs (Dwivedi et al., 2021). An area of research that is still in its infancy and has ample opportunities is the exploration of emerging developments in generative and conversational AI, and the theories surrounding them, and how we as humans build and maintain relationships with these AI technologies.

When exploring research agendas through the lens of the application of AI specifically in digital marketing, several themes become apparent. Firstly, the field is in need of modern and fit-for-purpose conceptual and theoretical frameworks that build on the existing knowledge of how we collect data about customers and then generate relevant marketing campaigns that are served via existing channels. The current hype around generative AI is creating uncertainty about how these theories and frameworks will hold up against the fast-changing environment of AI tools and platforms (Dwivedi et al., 2021). A systematic review of digital marketing definitions and terms is needed in the context of AI automation, augmentation and the potential for human replacement (Huang and Rust, 2022). Secondly, the issue of the personalisation–privacy paradox brings to the forefront the ethical issues associated with the developments in this technology (Gutierrez et al., 2019). Collecting, using and sharing customer data for marketing purposes has always raised privacy concerns, especially in the context of AI tools performing the tasks of collecting and analysing such data without clear understanding of the algorithmic process applied. Thirdly, as alluded to earlier, AI tools have the potential to augment, automate or completely replace human labour in some marketing domains, including creative tasks that were long believed to be out of the reach of AI and firmly in the domain of humans (Huang and Rust, 2022). The beliefs and attitudes of marketing professionals and customers play a vital role in the future successful adoption of these technologies beyond their technical capabilities and into the realm of relationships, which are constructed on an individual and social level.

Positivist research provides us with insights and trends derived from big data, and it quantifies the digital transformation occurring in organisations through experiments, surveys and questionnaires. Interpretivist research will connect that objective data with constructs of relationships, beliefs, attitudes and values. A traditional interpretivist viewpoint assumes that only human actions can be meaningful. We can no longer afford to distinguish human (social) actions from the actions of physical objects (AI) and assign meaning to one and not the other, as suggested by Schwandt (2003) more than 20 years ago. Meaning is constructed in the minds of humans, however, that meaning should be related to the actions of animate as well as inanimate objects, especially when these inanimate objects exhibit characteristics typically associated with human intelligence and behaviour.

The research paradigm most closely aligned to this type of enquiry is social constructionism, which is described as being “concerned with the nature of knowledge and how it is created and as such, it is unconcerned with ontological issues” (Andrews, 2012, p.39), while society is seen as both subjective and objective reality. Constructivism proposes that each individual mentally constructs meanings to events in isolation using purely cognitive processes, while social constructionism positions this “meaning creating” process in the context of the social group through the use of language and communication sustained by social processes (Young and Colin, 2004). In other words, knowledge and social action are inextricably linked in the meaning creation process.

It is worth clarifying that, although sharing common roots with the interpretivist approach to research, such as the focus on the process by which meaning is created, negotiated and sustained (Schwandt, 2003) and understanding the world from lived experiences, social constructionism is a distinct paradigm that views reality as both subjective and objective, whereas interpretivism values the human subjective experience but still tries to position it in an objective reality.

Objective reality is constructed through the interaction of people with the social world and, in turn, the social world influencing the views of people, which results in routinisation and habituation through repeating actions (Berger and Luckmann, 1967). These repeating actions allow people to adopt patterns of behaviour that allow them to be more innovative; prior knowledge becomes embedded in routine forming a general store of knowledge that society passes to the next generation as objective knowledge and reality. This objective reality is understood mostly through secondary socialisation and the direct interaction of the individual with wider society (Andrews, 2012).

According to Burr (2015), subjective reality is achieved through primary socialisation, which results from being assigned an identity and a place in society by close social connections (i.e., family) who communicate the objective reality of society and validate its meanings. This is achieved through the medium of language and conversation which makes thoughts, views and concepts visible to others in society, and provides the structure by which reality is experienced. Berger and Luckmann first proposed in 1967 that conversation is the primary method for constructing, modifying and maintaining subjective reality, which comprises concepts with shared meaning and understanding. This is accepted to such an extent that concepts do not need to be redefined each time they are used and they become a subjective reality that is taken for granted and passed on to other members of the close group.

To summarise the ontological, epistemological and reflexive view of social constructionism one can use Guzzini's (2005) useful frame of reference that demarcates this paradigm from its neighbours. The ontological claim of social constructionism is that social reality is constructed by both primary and secondary socialisation and is both subjective and objective (Berger and Luckmann, 1967; Lee, 2012). Being on either extreme of the subjective–objective continuum is a problem for studies adopting this paradigm. Adopting a strong objective position will result in the research ignoring constructed interpretations of the findings and will assume that what is reported is a true and faithful interpretation of an independent reality. A strong subjective stance will lead to conclusions that nothing can be known for definite, that there are multiple realities, and none have precedence over the other. Therefore, social constructionism makes no specific ontological claims, and the acceptance of subjective realities does not exclude the existence of objective ones. The epistemological claim is that knowledge is socially constructed. Knowledge and truth are created and not discovered by the mind (Schwandt, 2003). The belief that concepts are constructed rather than discovered and the belief that they correspond to something real in the world are not mutually exclusive. The medium by which concepts are created is language and conversation, which is neither subjective nor objective. It is not subjective since language exists independently of each individual person in a society; nor it is objective since it cannot exist outside our minds and our usage, which drives its existence and evolution. The reflexive view is that knowledge and reality are “mutually constitutive” (Guzzini, 2005, p.504). This means that the social construction of knowledge and the construction of social reality can be described as two sides of the same coin where social construction of knowledge can affect the construction of social reality and vice versa. The techniques employed on a micro level to achieve this effect are through linguistic feedback, such as ‘‘looping effects’’ (Hacking, 1995). Hacking posited that the categories we assign to someone’s identity can be redefined by the experiences of the people who adopt these classifications. Identity and classification become interlinked. On the macro level, when put in the context of cultures, social actors act on the basis of shared expectations, and this tends to reproduce these expectations resulting in “self-fulfilling prophecies” (Wendt 1999). In summary, the reflexive view postulates that there cannot be a meaningful reality without knowledge.

Further distinction needs to be made between the weak and strong versions of social constructionism as described by Smith (2010) and Schwandt (2003). From an ontological perspective both versions of social constructionism believe in “multiple realities”, they do however differ in their definition of what that means in practice. The weak version of social constructionism accepts the existence of one independent reality but insists that multiple interpretations are created to describe that reality. The strong version, on the other hand, would reject the existence of one objective raw reality, and build arguments based on the belief that there are multiple realities in the fashion of the “multiple universe” concept (Lee, 2012). In other words, there are multiple realities rather than multiple interpretations of one reality. Through the lens of epistemology, the difference between weak and strong constructivism is in the view of the existence of “brute facts” (Searle, 1995, p.62) where weak constructionism does not accept that all knowledge is socially constructed and at a basic level relates to an objective reality, while strong constructionism insists that all knowledge is socially constructed.

Social constructionism has been applied as a paradigm in studies of science and technology for many years, subjects dominated by the positivist paradigm, and as far back as 1979 when Latour and Woolgar published “*The social construction of scientific facts*”. The trend has continued with research into AI technologies primarily driven by computer scientists and academics (Restivo and Croissant, 2008). The proliferation of technologies has led researchers to re-evaluate their approach to academic enquiry and now social constructionism is being adopted more often; this adoption is based on two trends: (1) there are multiple technologies and tools that satisfy the requirements of a given task; and (2) that the choice of a particular technology is strongly influenced by beliefs, social influences and societal structure (Killick, 2004). From a social constructionist perspective, no technology adoption can be fully understood without understanding the choices people make individually or in groups and the underlying conscious and unconscious influences. As these choices are grounded in the objective functionality of these technologies, the paradigm more frequently adopted in this type of study is the weak form of social constructionism where objective reality is overlayed by subjective interpretations of it (Lynch, 2016).

3.3 Methodological Approach

Driven by the social constructionism paradigm, research aim, objectives and questions discussed thus far, the methodological strategy was heavily weighted towards qualitative methods, which aid understanding of intangible concepts such as trust, anthropomorphism and ethics (Creswell, 2014). There are a number of arguments that point to qualitative methods as the most suitable approach for this research study. Gerdes and Conn (2001) posited that qualitative methods aim to examine the whole rather than the parts as they involve examination of relationships between individuals and technology, individuals and their environments, and motivations that drive individual attitudes, beliefs and behaviours.

Qualitative research seeks to uncover concepts on the basis of the perceptions that social actors assign to them (Bell, Bryman and Harley, 2022). In practice, this means that the researcher becomes a part of their social world through the interpretations provided by the participants (Denzin and Lincoln, 2011). In this research context, the interviewer examines the experiences of students interacting with chatbots through employing think-aloud protocols while the participants engage with the technology as another social actor in an information gathering exercise; this is followed by an exploration of the background stories and perceptions that shape perception of the experience. The choice of words that participants use to convey their contextual realities of chatbot interactions means it is possible to interpret the meaning creation in a social context.

Additionally, qualitative methods do not impose rigid rules, strict boundaries or predefined procedures as some quantitative methodologies do. Using qualitative approaches to research allows for the collection of information containing “the richness of the personal experience" (Berrios and Lucca, 2006, p.181). The information consists of a complete description using the natural language of the phenomenon, which allows the research to be conducted in the natural environment where the phenomenon occurs and hence to observe the depth and richness of the experience. More importantly, the researcher does not start with preconceived ideas, but rather tries to uncover insights through the information collected and the analysis that follows, which allows for the researcher's critical judgement in interpreting the data (Denzin and Lincoln, 2011; Austin and Sutton, 2014).

In the realm of qualitative enquiry, a number of methods were considered potentially appropriate for this research topic, their merits, advantages and disadvantages were explored and compared through the framework proposed by Pouliot (2007). Three methods associated with a qualitative research approach were deemed most suited to the topic: grounded theory, narrative inquiry and case study.

Grounded theory was originally proposed by Glaser and Straus (1967) and later reformulated by Charmaz (2021) using constructivist perspectives. Constructivist grounded theory assumes the existence of multiple social realities, affirms the notion of mutual creation of knowledge and aims to provide interpretations of subjective meanings. This is a sequential method where one phase of the process determines the actions of the next phase. The researcher does not complete the literature review before gathering data but aims to develop a theory based on emerging insights from the views of the study participants (Creswell et al., 2003). The well-defined and rigorous process of grounded theory offers qualitative researchers a robust process in the development of frameworks that depict the relationships between concepts. Grounded theory was an early contender for this research. Selection of an approach was based on McCaslin and Scott's (2003) proposed "The five-questions method" for evaluating qualitative research methods. According to their framework, grounded theory would be deemed an appropriate method for this research if the researcher aims to “discover a theory for a single phenomenon of living as shared by others” (McCaslin and Scott, 2003, p.450). That definition certainly seemed appropriate in light of the fact that current theories relating to the topic of AI were developed before the capabilities of the technology reached their current heights. New theories on the subject may bring more value than adapting existing theories.

Alongside grounded theory, the case study method was also considered a plausible contender for this research. Case studies, particularly popular in research of business-related topics and thus relevant to the topic of this research study, allow for an in-depth understanding of participants’ motivations and behaviours during time-constrained experiences. A definition by Yin (2009, p.18) highlighted a case study’s strength, which is that it inductively investigates a complex social phenomenon in its real-life context, “especially when the boundaries between phenomenon and context are not clearly evident”. The more that a research question seeks to answer questions of “how” and “why” related to a social phenomenon, the more the case study becomes a strong contender for methodological choice for the researcher. The case study method allows for the research to retain the holistic characteristics of lived experiences either on an individual basis or in group settings, such as organisations, communities and cultures (Yin, 2009). Patton and Appelbaum (2003, p.63) also contributed by offering the perspective that case studies provide a holistic view of a process as opposed to the “reductionist-fragmented view” often offered by other methodologies. This is an important benefit as often the whole is “not the sum of its parts” (Gummesson, 1991). McCaslin and Scott’s (2003, p.450) proposed five-questions method for evaluating qualitative research methods indicated that a case study might suit research seeking to “discover what actually occurred and was experienced in a single lived event”, which suggested that a case study may be an appropriate method for evaluating the effects of chatbots on the student journey.

The third method considered for this research study was narrative inquiry, which is one of the more recently developed approaches; it was accepted as a research methodology in the 1990s. Narrative inquiry has evolved as a practice where narratives are collected for the purpose of understanding lived and told experiences in which people, individually and socially, live their lives through stories (Clandinin and Caine, 2008; Clandinin, 2022). The important word here being “experiences”; we rely on John Dewey's (1938) definition of experience as containing two specific criteria, interaction and continuity, which are enacted in a situation. Interaction refers to the notion that people are individuals but are always influenced by their social context. Continuity refers to the stance that experiences emerge out of previous experiences and lead to new experiences (Clandinin and Connelly, 2000). In addition, the meaning of narrative has evolved to incorporate a much wider range of meanings. For example, narrative now refers to almost anything that uses stories as data, narrative as content analysis or narrative as structure (Clandinin, 2022). Participants involved in research studies based on narrative inquiry tend to see themselves as co-creators. The collection of data usually utilises the methods of unstructured or semi-structured interviews and, where relevant, the exploration of documents and field notes. The challenge of using this methodology is in managing the variety of data types and sources and the interpretation that must follow in the analysis stage (Savin-Baden and Niekerk, 2007). Narrative inquiry seems particularly appropriate for this study considering the newly emerging capabilities of generative

AI tools, such as ChatGPT, to produce text that resembles human narrative to such a degree that it is almost impossible to tell the difference when compared side by side (Dwivedi et al., 2023; Rudolph, Tan and Tan, 2023).

Social constructivism has been accused of not defining a distinctive and unique methodology of its own, but borrowing methodological approaches used in social and political science. Adler (2002, p.109) went as far as to say that methodology is “the major missing link in constructivist theory and research”, while Checkel (2004) called for further debate about best practices. Pouliot (2007, p.359) answered the call in these scholars’ work and proposed a constructivist methodology which is named “sobjectivism”. The premise is that a methodology guided by the constructivist paradigm needs to develop not only objective knowledge about social life, which is “experience-distant”, but also subjective knowledge, which is “experience-near”. This approach stems from the dualistic view that the social construction of knowledge is the other side of the coin of social reality.
This constructivist methodology moves along the continuum of subjective knowledge at one end, which is collected from the meanings social agents attribute to their own reality, also referred to earlier as experience-near concepts, and objectified knowledge at the other end, which is constructed from standing back from a given situation by contextualising and historicising it, that is, experience-distant concepts (Geertz, 1987). Researchers should begin with an inductive enquiry into people’s realities, then objectify them through the stories’ context, and then seek further objectification through historicisation. Therefore, a constructivist methodology needs to be “inductive, interpretive, and historical” so it develops not only subjective knowledge but also objectified knowledge (Pouliot, 2007, p.360).

The first step in the research methodology is using inductive analysis consisting of recording and analysing the meanings that participants attribute to their reality. In the context of this research this was achieved through the “chatbot experience” where participants were presented with an opportunity to interact live with a publicly available university chatbot and attempt to extract information useful to their personal interests and circumstances. All of the three approaches to qualitative research considered earlier – grounded theory, case study and narrative inquiry – are suitable for this step. All three would provide details of the subjective lived experiences of participants with various degrees of contextual information that could be used during the later analysis stage.

The second step of the methodology is to apply interpretive techniques with the aim of incorporating meanings that also explain context and social life. For example, social, cultural and language meanings make it possible to understand the meaning of idioms, proverb or cultural expressions specific to a given group. This additional richer meaning is found not in the exact words contained in the narrative, but in the intersubjective context which is interpreted and objectifies the subjective meaning. To objectify meanings is to contextualise what something means not just for a specific person but in a larger social context (Pouliot, 2007). In the context of this research the participants were invited to describe their own beliefs and attitudes to the chatbot technologies and to contextualise this experience with their preconceived beliefs and values. From the three methodologies considered earlier, only two – the case study and narrative inquiry – are suitable for this second step in the constructivist methodology approach and can provide information suitable for interpretation most effectively.

The third and final step in the proposed methodology is to recognise that meanings continuously evolve over time. A historical approach can track the evolutionary process that social meanings undergo; to trace them the researcher needs to build a narrative, that is, an evolving account that details the story as it unfolds over time (Polkinghorne, 1988). Historicisation, as a third filter of analysis, provides new and objectified knowledge in the form of a narrative that depicts the dynamic unfolding of a story containing historical processes that show the evolution of the current reality. In the context of this research, historicisation was achieved by asking participants to recall their earliest interactions with chatbots and how those interactions changed over time to the present day. From the three methods considered thus far, narrative inquiry, being a chronological account of someone's experiences in a particular personal and social context, together with grounded theory would be best suited to provide such insights because they both produce narrative explanations that are retrospective in nature.

Considering the three steps of the methodology described above, it was thought that narrative inquiry best addressed the aim and objectives of this research and the benefits of applying this methodological framework could be fully realised so that subjective meanings are objectified through both contextual and historical lenses.

In choosing narrative inquiry as the methodology for this research study, the difficulties and challenges had to be fully considered and acknowledged. Savin-Baden and Niekerk (2007) proposed a comprehensive list of pros and cons for researchers to consider before embarking on the path of a narrative inquiry-powered research methodology. On the positive side, most people are happy to share stories about themselves so finding participants would be relatively easy. Secondly, narrative inquiry provides opportunities for collecting "thick description" full of in-depth subjective and contextual meanings as this occurs easily in narrated stories (Savin-Baden and Niekerk, 2007, p.466). Thirdly, people tend to be truthful when retelling their stories and experiences or, if they are not, that becomes apparent when the data are interpreted and analysed.

Challenges with narrative inquiry may stem from the process where the researcher in the role of the listener, and the participant in the role of the narrator, co-create the narrative. However, distinction needs to be made about whose story it is in the end and how it is interpreted and reinterpreted. Secondly, it is often difficult to decide the relationship between the subjective narrative account of an individual and the objectified knowledge that social, cultural and organisational contexts provide. And thirdly, when more than 10 stories have been collected it becomes more difficult to analyse them in a such way that the interpretations are coherent, and people's stories are not fragmented by the analysis applied. Therefore, this limitation informed the sample size for this study as well as the contextual questions posed to each participant in order to create a personal summary of each person and their story.

Any conversation with a CA can be classified as a personal experience between a human being and an algorithm for the purpose of knowledge discovery on a specific topic. Narrative inquiry aims to understand the motivations of potential students to initiate the conversation, as well as the social circumstances that govern the process. This methodology's strength of collecting rich data about students' experiences confirmed it to be the most appropriate approach to understanding the relationships between an HEI and its prospective students. Narrative inquiry preserves the contextual information that informs the students' point of view and exposes the socio-cultural influences that may influence their attitudes, beliefs and values.

3.4 Sample Selection and Size

The need to choose the most suitable sampling technique for this study was driven by the research aim and objectives to investigate the effects a chatbot may have on the student recruitment process in HEIs. The populations that have vested interest and knowledge in the subject matter are, on the one side, potential students gathering information about their options of university courses and degrees at either undergraduate (UG) or postgraduate (PG) level, and, on the other side, the marketing professionals in the HEIs deciding on the deployment of a marketing communication channel in the form of a CA. Therefore, the target population could be defined as three distinct groups of individuals. First, was the group of individuals who were currently considering applying for UG degrees in a UK HEI. They may still be in secondary education or studying foundation programmes or taking time away from education but not have studied any subject to FHEQ (The Framework for Higher Education Qualifications of Degree-Awarding Bodies in England, Wales and Northern Ireland) Level 4. The second group of participants comprised individuals who have completed an UG degree and are actively seeking information about their PG options either in a taught or research-based PG programme. The third group consisted of individuals currently working in HEIs at a role in the marketing department directly linked with the tasks of student recruitment.

As the approach to this research was qualitative, the probability of each case being selected was not known in advance, the objectives did not require the extrapolation of statistical inferences about the characteristics of the population, and hence only non-probability sampling techniques were considered (Saunders, Lewis and Thornhill, 2019). Out of the available choices in non-probability sampling techniques, purposeful sampling was selected for this study because it allows for the collection of rich data that provide both subjective and objectified information in line with the constructivist methodology selected for this research (Palinkas et al., 2015; Duan et al., 2015). Patton (2015) proposed over 40 strategies for selecting a sample, which were grouped in eight categories to differentiate between their strengths and weaknesses. For the purpose of this research, a combination of four strategies was applied. Firstly, homogeneous sampling was applied to the researcher's personal network by selecting cases that met the sampling criteria (Patton, 2015). The criteria applied aimed to select cases that provide rich data during the chatbot experience and interview part of the process. The inclusion criteria were: (1) individuals 17+ years who are currently searching for UG courses to study in a UK HEI, (2) individuals who are currently searching for PG courses to study in a UK HEI and (3) individuals that who currently working in a marketing role in a UK HEI. This approach produced mixed results where some of the groups had an insufficient number of participants and one group had more participants than were required. Consequently, snowball sampling was deployed to identify further suitable cases that fit within the first and second selection criteria. This technique is particularly valuable when the researcher experiences difficulty in making initial contact with the target group (Saunders, Lewis and Thornhill, 2019; Naderifar, Goli and Ghaljaie, 2017). Participants were asked to identify others in their network that met these criteria and introduce them to the researcher. The termination point of the snowball sampling was determined by saturation or redundancy sampling was deployed as analysis of the data was performed in parallel with the data collection and, as the themes emerged, the point was reached where nothing new was being discovered. For the group with an excess of participants, purposeful random sampling was applied to the group of participants that met the third inclusion criterion. A group of 15 marketing professionals was identified as potential participants from the researcher's personal network. From those, eight were randomly selected to take part in the research. This sampling technique was selected due to the potential number of participants exceeding the available time and resources (Patton, 2015).

The sample size of 24 comprising of 8 participants in each selection criterion may seem small compared to other studies with hundreds of respondents. In non-probability sampling, unlike probability sampling, there is no consensus on what the size of an adequate sample is. What is more important is the relationship between the sampling technique chosen and the purpose of the research study (Saunders, Lewis and Thornhill, 2019). Marshall (1996) suggested that a large sample does not guarantee a comprehensive conceptualisation of the phenomenon. Additionally, Marshall (1996) pointed to the possibility that a large sample size might obscure some important information from participants. This implies that if the research aim is to obtain a depth of understanding of a particular phenomenon, then working with a large sample size may defeat the purpose of the research. This approach seemed to be in line with the sample size of between 15 and 60 recommended by qualitative researchers (Saunders, Lewis and Thornhill, 2019; Patton 2015).

The data saturation point was one of the sampling techniques deployed in this research (Marshall, 1996; Patton 2015). Nielsen and Landauer (1993) went as far as to provide a mathematical model claiming that six participants in a qualitative study can uncover 80% of the information needed to solve a problem. In light of this, eight participants were invited in each category to take part, which comprises a fully justified sample size.

3.5 Data Collection Method

Prior to commencing data collection, two steps were performed to ensure that the data collected were rich and detailed. Firstly, the websites of 175 UK universities and colleges were screened for the presence of a publicly available CA. Of those, 21 HEIs were found to have a form of a chatbot either on their home page or on an internal web page, such as the “Study” page. Analysis was carried out on all 21 CAs in the form of adopting the identity of a student searching for course or university information and performing a number of simulated conversations to identify the type of CA available and the scope of their capabilities. Of the 21 websites, 6 had a chatbot allowing for a free-text entry method, sometimes combined with pre-set options, while the remaining 15 chatbots were only of the decision-tree type where users were only allowed to click on options without the possibility to type their own questions. After repeat testing of all available chatbots, six were shortlisted to be used during the interviews; the chatbot experience with two of the chatbots was entirely free text, three were a combination of free text and options, and one was entirely based on options. The intention for the interviews was to ask participants to interact with three chatbots, one of each type, and the remaining chatbots to be used as a backup in case technical difficulties were experienced during the live interview. All participants engaged with at least three chatbots and some with four during their interviews. Table 3.1 provides further detail on the final choice of chatbots included in the task-based part of the interview.

University	Website	Method of contacting

University of Aberdeen	https://www.abdn.ac.uk/	free text guessing questions, providing pages
Anglia Ruskin University, Cambridge	https://aru.ac.uk/	free text and then gives options
Bournemouth University	https://www.bournemouth.ac.uk/	free text
Durham University, Durham and Stockton-on-Tees (Queen's Campus)	https://www.durham.ac.uk/study/undergraduate/	AI
University of Northampton	https://www.northampton.ac.uk/	type free text, give direction to web page
Solent University	https://www.solent.ac.uk/	decision tree

Table 3.1 Final Selection of Conversational Agents for Task-Based interviews (Source: Author, 2024)

For this task-based part of the interview think-aloud protocols were deployed as the method of data collection to gain insights into the participants' thought processes and decision-making strategies while interacting with the selected CAs. Think-aloud protocols are designed to encourage participants to verbalise their thoughts as they engage with the task to provide a real-time account of their attitudes, beliefs and values (Ericsson and Simon, 2003). This approach allows participants to verbalise their problem-solving techniques, their strategies to navigate challenges and to articulate their motivations. Integrating think-aloud protocols into the framework of task-based interviews allows boundaries to be imposed around the scope of the participants' reflection and leads to deep understanding of intentions to use CAs. This approach stems from usability studies in marketing and engineering where participants are observed while interacting with a product and discussing their experiences (Nielsen, 1994). Following this methodology, collecting information via semi-structured interviews usually allows the interviewer to probe for the deeper meaning and specific attitudes that emerge from the task. This combination of approaches can enrich the collected data, and further clarification can be obtained about specific reasoning, alternative approaches the participants may have considered and any past experiences that may have influenced the completion of the task.

The second step in preparation for the interviews involved the curation of the questions to be added to the questionnaire that would guide the conversation. The initial selection of questions was formulated to directly address the research questions of this study. Furthermore, the questions suggested for future study from Puntoni et al. (2021) were added to create a link with the identified research gap. Finally, the research questions were given as a prompt to ChatGPT, which was asked to generate questions for a semi-structured interview. A small number of new and unique questions were added to the final selection. The final selection of questions was the same for the UG and PG groups of students. There were 28 potential questions that were split into five topics. At the start of the interview all participants were asked to answer three classification questions, which were followed by seven questions relating directly to their experience interacting with the bots. Then the questions widened the discussion to more general topics and explored the participants' perceptions of the usefulness and ease of use of the technology, their general attitudes and beliefs towards this technology, as well as their beliefs about the future use of the technology. As these were semi-structured interviews, not all questions were asked of all participants, and clarification or expansion questions were added based on the answer received.

The interview questions for the marketing professionals were chosen to a great degree to be a variation of the questions asked to the student participants. The 27 possible questions also started with a few classification questions followed by questions relating to the chatbot experience. The remaining questions were augmented to enquire about the opinions of these participants from a marketing and university perspective rather than a user perspective. Questions around bot performance, reporting and metrics were added to represent views relating to "behind the scenes" considerations usually hidden from the student participants. The marketing professionals suggested follow-up questions of their own in the course of an interview, such as the use of ChatGPT for comparison or to demonstrate chatbots from other industries.

The one-to-one interviews were conducted between November 2023 and February 2024 via MS Teams. The interviews lasted between 45 minutes and 75 minutes, which is in line with Robson and McCartan's (2016) suggested timeframe of between 30 and 60 minutes. The first 20 to 30 minutes were usually dedicated to the chatbot experience where participants were asked to interact with the chatbots in a natural way and to perform actions as if they were doing the exercise without the researcher present. They were encouraged to articulate their thoughts and feelings as they were interacting with the bots and the researcher asked some questions to direct their attention to particular features they may not have noticed. The remaining time was dedicated to more general questions that explored past experiences with chatbots, attitudes and beliefs about the technology, compared the experience during the interview with previous chatbot conversations, and their beliefs about the future use of the technology. Some participants with more extensive chatbot experience were also asked to interact with Gemini or ChatGPT and compare the experience in the moment. For each interview Otter.ai was used to provide recording and transcription support allowing for voice and screen capture that was used later to clean and finalise the transcripts.

The comments of the 24 participants were assigned to one of three groups based on the classification question: their interest in studying a UG or PG programme or they were a marketing professional from the HE sector. A breakdown of the participants can be seen in Table 3.2 below:

Participants	Age (years)	Gender	Type
1	18–24	female	Undergraduate
2	36–50	male	Undergraduate
3	17	female	Undergraduate
4	17	male	Undergraduate
5	18–24	male	Undergraduate
6	18–24	female	Undergraduate
7	18–24	male	Undergraduate
8	17	female	Undergraduate
9	36–50	female	Postgraduate
10	25–35	female	Postgraduate
11	25–35	female	Postgraduate
12	18–24	female	Postgraduate
13	36–50	female	Postgraduate
14	25–35	male	Postgraduate
15	50+	female	Postgraduate
16	36–50	female	Postgraduate
17	15 years in HE	female	Marketing Professional
18	10 years in HE	female	Marketing Professional
19	13 years in HE	female	Marketing Professional
20	15 years in HE	female	Marketing Professional
21	10 years in HE	female	Marketing Professional
22	15 years in HE	female	Marketing Professional
23	10 years in HE	male	Marketing Professional
24	43 years in HE	male	Marketing Professional

Table 3.2 Interview Participants' Data (Source: Author, 2024)

3.6 Researcher Reflexivity

This research journey started as a natural next step following the completion of my master's degree in data analytics and marketing where the dissertation topic chosen was in the similar field of chatbot application in the marketing context. My personal interest in chatbots had begun several months earlier when I had the opportunity to participate in the research, design and launch of a chatbot for the organisation I was working for at the time and really immerse myself in the practical applications of these new and emerging technologies in real organisations. This experience provoked curiosity in me not only about the technical side of how chatbots work in practice, but also from a more theoretical perspective to try to understand the more intangible factors that made a chatbot project successful or not. This experience led me to research the academic literature available at the time (2020), and to complete my master's dissertation.

Progressing the topic to doctoral level research was the obvious next step for me as my curiosity continued to grow as the technology powering conversational AI tools continued to evolve. During my research in 2020 hardly anyone had heard of chatbots, and were even less familiar with their capabilities. In 2023/24 we find ourselves in a very different environment where we are grappling with the profound effects the launch of ChatGPT has had on professional life and education, and the new tools that are now available and free for all to harness the power of LLMs. This development has made this doctoral research even more challenging as the academic landscape has profoundly changed since the start of my research in 2021.

Several revisions have been done to this thesis to attempt to capture the latest thinking on the topic and to use current data as the foundation for this work.

Having spent a long time working in industry and applying technical interventions as part of my job role, I had always believed that when I embarked on academic research I would find the pragmatism paradigm to be the most aligned to my ontological and epistemological views. Perhaps that is the reason why I implemented a mixed methods approach in my master's degree where I used both a questionnaire to extrapolate quantitative data about the state of the topic, and semi-structured interviews where I attempted to gather qualitative views from the participants. With what I thought to be a very holistic approach to the topic, I did capture answers to "what" and "how" questions; however, the research was much weaker in answering the "why" questions, which may have revealed deeper truths about the benefits and challenges of these new conversational AI tools.

After consulting with academics in the marketing field and discussing my approach to the next stage of my research, I was introduced to the benefits of the social constructionism paradigm that seemed to better fit the kind of questions I was seeking to answer. I familiarised myself with the works of Maxwell (2013), Denzin and Lincoln (2011) and Holstein and Gubrium (2013), which helped me to fully appreciate the interpretivist ontology and, more specifically, the characteristics of constructivism and social constructionism. Social constructionism allows the research to still retain the view of how social norms and developments shape the individual's views and attitudes towards using chatbots, as well as seek to answer the "why" questions that underpin this research. Focusing on semi-structured interviews with both users of chatbots and the people who work behind the scenes to deploy them would be more likely to produce knowledge that would form the foundation of a conceptual framework and it would be more likely to withstand the rapid changes observed in the development of the technology powering conversational AI.

From the perspective of the academic literature, the work of Huang and Rust since 2018 proved particularly interesting and relevant to this research because they have closely followed the development of AI tools and their implementation in the field of marketing in an attempt to predict how they may fundamentally change the job of marketers in the years to come. Starting with “Artificial intelligence in Service” (Huang and Rust, 2018) and continuing with “A framework for Collaborative Artificial Intelligence in Marketing” (Huang and Rust, 2022), their research has provided steppingstones for other researchers to build on their initial findings and theories, which is the intention of this study.

Understanding the impact of AI-powered tools has become one of my intellectual passions beyond the scope of this research and has provided me with a mission to continue exploring this field beyond the end of this endeavour. I foresee AI research becoming an integral part of my future academic career development, being fully aware of issues such as reliability, validity and generalisability, which are explored in the next section and justified in the context of qualitative research approaches.

3.7 Research Quality

The issue of research quality in qualitative studies needs to be examined through the frameworks developed by scholars such as Maxwell (2013) and Denzin and Lincoln (2011). These frameworks provide a model that corresponds to the more popular terminologies of validity, reliability and generalisability, which are derived from the positivist paradigm that dominated academic research for many years. In qualitative research the construction of a conceptual framework is central to the research design as demonstrated in the framework provided by Morse and Mitcham (2002) and Maxwell (2013). Both pieces of research posit that a conceptual framework adds to the rigour and quality of research, but it should be used carefully and not used to the extent that it is used deductively, as that would contradict the inductive nature of qualitative research and interpretivist paradigms. In other words, qualitative research should be able to generate a conceptual framework that provides guidance to the researcher about the questions that can be explored but not become so rigid that it feels like testing a hypothesis, which will drift the research into deductive territory (Johnson, Adkins and Chauvin, 2020). Since the creation of a conceptual framework is considered a core qualitative research goal, the qualitative research design for this study was steered towards creating a conceptual framework.

What Maxwell (2013) called “validity” in qualitative research, Denzin and Lincoln (2011) called “credibility”. This is in fact one of the four criteria they propose to substitute the positivist “validity”, “reliability” and “generalisability” criteria of quantitative research with the concept of “trustworthiness”. The other three are “transferability”, representing “generalisability”, “dependability” which is aligned with “reliability” and “confirmability” which also links to the criterion of “validity”. Credibility refers to the efforts the researcher has made to provide supporting evidence that the data collection and analysis produce results that accurately represent the views of the participants; transferability ensures that the researcher has provided enough contextual information so that readers can determine if the findings of the study and subsequent conceptual framework are relevant to their own circumstances; dependability refers to the information provided relating to the research process that will allow other researchers to repeat it; and confirmability refers to evidence that the findings are indeed based on the views of the participants and not based on the biases of the researcher.

To address the two main types of threats to the four criteria of trustworthiness, this research has been designed with mitigating steps throughout the research process (Maxwell, 2013). The first identified threat is researcher bias, which can manifest itself either in the selection of participants and data that fit the researcher's preconceived theory of the topic or the data stands out from general data (Miles and Huberman, 1994). The second threat is reactivity, which refers to the influence the researcher may have on their participants, especially during data collection methods, such as interviews, where the researcher may pose leading questions (Hammersley and Atkinson, 1995).

The mitigating steps that address these validity threats begin with the choice of participants. Purposeful sampling was selected as an approach for two main reasons. The marketing professionals who were interviewed were all at a level of manager or above. This job title denotes that these individuals have been in the marketing profession for a number of years and have been able to observe in practice the recent developments in AI-powered tools that have augmented the marketing profession. Even though a longitudinal study is not practical within the scope of this research, interviewing individuals with some years of experience in the marketing industry provided a longer-term view of this phenomenon. The application of narrative inquiry allowed for the collection of historical data as well as rich data that provided rich context to satisfy the criteria of transferability. Rich data were also obtained from the other group of participants – the prospective students

– by allowing them to immerse themselves in the act of communicating with a chatbot and subsequently to reflect on previous chatbot conversation experiences; this provided detailed and varied data that painted a full and vivid picture of the experience (Becker, 1971).

Another step in the data collection process that should minimise threats to trustworthiness is the step where participants were asked to review the transcripts of their interviews and provide feedback about the conclusions derived from the interviews (Bryman, 2003; Guba and Lincoln, 1994). This step helps the researcher to rule out the possibility of misinterpreting the meaning that the participants intended in their narrative, to accurately represent their perspectives and for participants "to make their own checks and judgements", ruling out the creep of the researcher's bias in the data used for analysis (Potter and Edwards, 2001). This step was aimed at addressing the credibility and confirmability criteria as defined by Denzin and Lincoln (2011).

By choosing participants from three distinct groups – those searching for a UG course (perhaps younger and less definite in their course choices), those searching for PG courses (perhaps older and more mature), and marketing professionals from the HEI sector – the researcher attempted to apply triangulation to the data collected and include a wide range of individuals who could provide diverse perspectives on the topic. Triangulation directly addresses the criteria of dependability and transferability and provides better evidence for the application of knowledge in different contexts to the one studied in this research.

Finally, the threat to validity called "internal generalisability" (Maxwell, 2013) is described as research credibility that should be extended to all members of the sampled group. This study was limited to UK-based HEIs that may be recruiting students both domestically and internationally. There is no reliable way to know if the findings of this study are applicable to all 175 HEIs in the UK or indeed to any institutions further afield. In an attempt to increase the credibility of this study, the websites of all 175 HEIs were inspected for the presence of chatbots. Of the 21 chatbots discovered in late 2023, 6 were shortlisted as options to be used during the interview process. Participants were invited to experience three or four of the shortlisted chatbots for the experience part of their interviews. This step of deliberate randomness in the choice of a chatbot aimed to both limit the researcher's bias in what may be considered a good chatbot experience and to increase the internal generalisability of the study.

3.8 Ethical Considerations

There is no one single set of rules that guides ethics in any research project. In fact, most of the time the rules are "contextually driven and simultaneously contextually bound" (Soobrayan, 2003, p.107). The ethics considerations for this research can be described as coming from internal and external perspectives or, in the words of Guillemin and Gillam (2004, p.261), ethics can be classified as either "procedural" or "ethics in practice". Procedural ethics refers to the process of seeking approval from relevant ethics committees to undertake research with humans, while ethics in practice refers to the everyday ethical considerations and decisions that the researcher faces as they conduct their research.

Firstly, this research follows the ethical guidelines of two universities – the University of Worcester and The University of Law. University of Worcester's ethical guidelines were observed when choosing participant groups, especially in light of the fact that some participants may be under 18 years of age and hence considered children. For that reason, differentiated information sheets were created for under 18s, their parents, adults and marketing professionals. Consequently, differentiated consent forms were also created for parents and adults and a corresponding assent form for children. The University of Law’s ethics committee also had to be satisfied with the merit of this study. As the researcher’s employer, it provided access to students who fit the participant categories for this research. Both universities received copies of information sheets, consent and assent forms, potential questions to be used in the semi-structured interviews and templates of the communication that will be used to recruit participants. Specific guidance was provided for the technology platforms to be used for the interviews and the data storage and destruction parameters. The British Educational Research Association’s *Ethical Guidelines for Educational Research* were incorporated in the documentation to reflect best practices for consent, incentives, privacy, data storage and others.

To avoid a conflict of interest, participants from the group of marketing professionals were not asked to disclose the institution they work for, but rather to discuss their observations, beliefs, attitudes and experiences from a personal perspective. Participation in the study was entirely voluntary and the participants could withdraw at any point up to approving the inclusion of the transcript of their interview in the data analysis stage. In cases of withdrawal, all information pertaining to the participant would be destroyed. The personal information of the participants was anonymised and will be destroyed at the end of the study. The participants were provided with information about the output of the study and were offered the opportunity to receive a copy of the final approved research.

Ethical considerations from an internal perspective can be described as the consequence of the reflexivity applied throughout this research project. From choosing the topic of this research, to finalising sampling techniques and choosing the right participants for the interviews, to the selection of the most relevant extant literature, every step of the research process was interwoven with ethical decisions that could either strengthen the trustworthiness of this research or create doubt about its credibility or any of the other three criteria for research quality. These are certainly not ethical decisions for the ethics committees of universities as many cannot be anticipated or even considered ethical dilemmas at the time. The process applied to this research was driven by the researcher's personal sense of integrity and general propensity to follow established rules as well as the moral codes of today's society.

3.9 Summary

This chapter described the research design approach for this study by firstly justifying the chosen paradigm and comparing it to other paradigms that may have also been appropriate for the research question. The chapter continued by presenting the appropriateness of the qualitative approach and defining what is considered to be a constructivist methodology; three possible methods for qualitative research were explored and led to the selection of narrative inquiry as the preferred method of data collection. Sampling methods and sample size were discussed in the context of the chosen methodology. The section on researcher reflexivity provided context for the methods and approaches chosen for this study, which was followed by an exploration of the various methods to ensure research quality and ethical robustness.

CHAPTER FOUR
ANALYSIS AND FINDINGS

4.1 Introduction

The previous chapter outlined and justified the research design that underpins the structure of this research study. It clarified the reasons for selecting social constructionism as the guiding paradigm which, in turn, drove the decision to choose qualitative methods for selecting the type of data collected, the quality and quantity of participants selected, and the approach to analysis which is presented in this chapter.

This chapter presents the analysis carried out on the interview responses from 24 participants from three distinct groups who provided their time to be observed interacting with university chatbots and then shared their views in semi-structured interviews. This chapter in particular provides the answers to the second and third research questions: “*What attitudes, beliefs and intentions contribute to users’ successful interaction with CAs in the information gathering stage of the student journey” and “What are the conditions necessary for successful human–machine interaction with CAs that would result in an improved student experience at the information gathering stage?”*

Firstly, the chapter tackles the rationale for the application of thematic analysis and presents the six-step systematic process followed in this research project. As a result, the study developed four major themes consisting of 10 to 15 concepts that comprise the spectrum of the topic investigated. The interpretation of the attitudes, beliefs and values of the participants was approached through think-aloud protocols during engagement with a task and narrative analysis with the aim to construct a thematic network diagram that represents the connections between the themes and codes analysed in this chapter. The implications of the data findings are discussed and the connections between the themes and literature are highlighted.

4.2 Rationale and Application of Thematic Analysis

Based on the interpretative, qualitative and social constructionism methodologies, this study selected thematic analysis as the most appropriate approach to extracting themes from the data without losing sight of the context in which the data were collected. After exploring the original approach to thematic analysis defined by Braun and Clark (2006, 2012, 2013) as “a method for systematically identifying, organising, and offering insight into patterns of meaning (themes) across a data set” (Braun and Clark, 2012, p.57), thematic analysis appeared to be the most appropriate approach amongst the other textual analysis approaches available to qualitative researchers. Discovering patterns of meaning “across a data set” revealed the necessary links to make sense of and discover collective and shared meanings across the three groups of participants interviewed for this research. Thematic analysis provided the basis for identifying what was common to the way participants interacted with CAs or talked about their views, then the importance of these commonalities to the research objectives and research questions explored in this work was identified. This was especially pertinent when looking to discover key factors influencing students’ decision making at the start of their student journey or the beliefs that may make them more or less reluctant to make those decisions based on the information provided by HEI CAs.

As the extant literature on the specific topic of using CAs for the purpose of student recruitment was quite limited, there were no obvious or well-defined themes that could have underpinned efforts to carry out deductive thematic analysis. Therefore, there were very few preconceptions in the outlook of the researcher that could have potentially interfered with the identification of key themes (Morse and Mitcham, 2002). As a consequence, this research adopted the inductive approach of “goal-free” evaluation (Scriven, 1991) where themes emerge from the rich data collected and are then synthesised in the creation of an appropriate conceptual framework, which constituted the fourth objective of this research.

With the aim of creating a conceptual framework and imbuing this research with more rigour, this research adopted the more comprehensive and systematic step-by-step thematic analysis process developed by Naeem et al. (2023). The process is deemed to be “systematic” as it employs sequential and structured steps while interpreting the research data that builds one step onto the previous to ensure that the interpretation is consistent and comprehensive.

Step one defines the process of transcribing the data and familiarising oneself with the content. In this step, statements and quotations are chosen to represent pertinent views. While conducting this step, the value derived is the opportunity to examine the data two more times after the interview. By listening to the recordings and cleaning the transcripts that were created with the help of an AI tool, the researcher was able to really delve deep into the meaning of each sentence and derive not only the “semantic” (surface) meaning of what was said, but also the “latent” (deeper hidden) meaning that reveals underlying ideas and assumptions

(Ozuem, Willis and Howell, 2022, p.147). In Figure 4.1 below, there is an example of a transcript created by Otter.ai and manually cleaned up by the researcher.

Dessy Ohanians
So, the bot didn't pick up that you typed MBA, it still went with a very general answer. So, if you type below again in the free text, "I'm interested in a name in an MBA", would it pick that?

Participant
"I'm interested in an MBA"

Dessy Ohanians
Just put it like that and see when the bot answers.

Participant
No, basically the same information. "It's great you'd like to study in master's degree. If you go here (link), you'll find a whole list of all of our masters' courses and lots of other useful information". And then I have options that's useful or not useful, which in our case, I find not useful.

Dessy Ohanians
Do you want to ask another question? Maybe around fees, bursaries, anything around that?

Participant
Yes, I will give it a go.

Dessy Ohanians
But ask specifically for the MBA, not in general.

Figure 4.1 Transcript Sample (Source: Author, 2024)

Step two is the stage where another pass is made on the selected quotes; keywords are selected to represent recurring views or beliefs about a specific topic. These keywords are selected to encapsulate the participants' thoughts and experiences while interacting with the bots as well as their more general attitudes to CAs that have been formed prior to the day of the interview. In this particular research, steps one and two overlapped at times. While selecting quotes, a preliminary judgement was made on what might be the relevant keywords that brought the statement to life. Once the quotes were selected, a second evaluation was carried out to determine whether the originally highlighted keywords were indeed the most appropriate ones to select using the 6Rs criteria proposed by Naeem et al. (2023): realness, richness, repetition, rationale, repartee, regal. The implementation of this step is demonstrated in the sample provided in Table 4.1.

Keywords	**Quotes**
nice gesture, brief introduction, quick answer, depressing, enough information, short, informative	**P1 -** I knew what I had to do, but it's always a nice gesture to see a welcome message. **P2 -** I think a brief introduction is probably best, because if people are using chatbot, they're usually looking for quite a quick answer to that question. So, I think if people have a lot to read, then that can be quite inconvenient. But if people don't get any greeting, then it feels really obvious that you're not speaking to a person and some people don't enjoy that. **P3 -** At least a welcome like: "My name is Sam". It could have been there, because the blank page is just depressing, and you don't know what to say or type. It just says: "Type your message here". It's strange. It should have been: "Welcome. Ask me any questions". Something like this. **P4 -** Yeah. I think it's best to know enough information as I can see, you can chat with the bots 24/7 or with a real person live and it says what time you can chat with them. I think that's quite nice thing to add. **P5 -** I liked the welcome message. It was short, informative, good. When I wrote my name in, it welcomed me. It was good. I liked it.

Table 4.1 Keywords Selection (Source: Author, 2024)

Step three describes the process of extracting codes from the identified keywords with the aim to assign a summative and meaning-capturing short phrase that leads to indexing the information into a more theoretical and conceptual form (Creswell, 2020). These codes are then analysed for their relevance and significance to the aims and objectives of the research, logical links between the codes, overlaps and similarities and the emergence of more universal themes. For this research in particular, several codes emerged that were specific to one of the participant groups and other codes on the same topic for the other groups. A decision had to be made on whether these codes did indeed overlap enough to be merged into one code or they represented sufficiently different views and they should remain separate. The demarcation line between them sometimes was so blurred that the decision could have been justified in either direction. Once again, the 6R model for coding proposed by Naeem et al. (2022) was applied to the codes to ensure they were robust, reflective, resplendent, relevant, radical and righteous. Table 4.2 provides a sample of one of the codes being constructed from the multiple keywords and quotes.

Codes	Keywords	Quotes
layout/design	prefer side-to-side scrolling, compare, takes ages, space on screen, quick to see, colour, text, broken down, short, taking its time, a lot of information	**P1** - I personally prefer the side-to-side scrolling because it's easier to track it. I think sometimes a drop-down function where you can go collapse is better because sometimes there's a lot of information in one block here. I think it's good to see the options available at a glance because then you can click on the link and then find out more. **P2** - I might just use a chatbot if I want to know something, but sometimes I find that a chatbot takes up a lot of space on the screen. This one is hard to minimise, and it gets in the way. Sometimes, not always. I would use a chatbot but sometimes it takes ages to get the information. **P2** - I personally prefer X university just because I felt that it was quite quick to see, the colour and the text and the way it's formatted was quite short, and it was quite easily broken down for me to process the information. **P3** - Oh my gosh, there's a lot, that's why it was taking its time. **P4** - Oh, it goes away and comes back. Because you see, for me, that's minimises, not closes, like I am finished, I don't ever want you back again. The cross means I'm done. So, that's interesting. I wouldn't have necessarily understood to minimise it. **P5** - I think it's all going to come down to how good the designer is. The X university designer has obviously thought it through really well. I like the ones where the chat comes with you. I wouldn't have got that the cross button just minimizes it instead of making it go away. I'd be interested to know whether the chatbots keep a record of all the chats they have and whether the universities ever go over to see what people are asking about and who's contacting them? **P6** - This scrolling thing – it's a negative. It needs to look at the options based on my needs. It doesn't save me time this way. **P7** - If you look at this page as I'm scrolling now for X university the information is in long reading points. Normally in a chat you don't expect this. It's just like going through the website itself. What is the

		advantage of a chatbot if it's just summarising, and not making everything easier for us. But it is just giving me a lot of information to read in this small window. **P8 -** I don't like that side-to-side scrolling. Do I like it? I don't know. It's different. **P8 -** That's good. Yeah, it does, it takes you through. Even if you open multiple tabs, it will stay with you. **P8 -** I think visually and aesthetically, the X university one is a bit more appealing. To me, it looks more appealing. The Y university one could be a bank, it's a little bit corporate looking. And the Z university one looks a little bit cheaper. I think it's just the font they use and the colours they use.

Table 4.2 Sample of a Code Construction (Source: Author, 2024)

Step four marks the transition from the more practical and detailed extraction of codes to the more abstract and theoretical creation of themes. In this research, the fourth step of theme development progressed through two distinct stages. In the initial stage of coding, categories emerged that captured the semantic (surface) themes that were immediately obvious from the similarities in the codes. They included quite basic, descriptive and factual categories such as trust, effectiveness, advantages, disadvantages, future, anthropomorphism and desired features. As these categories did not capture the “latent” and more abstract themes required to answer the research questions, a second stage of analysis was deployed where three actions aided the definition of the final four themes. Firstly, all available codes were randomised and fed into a prompt into ChatGPT. The prompt instructed ChatGPT to identify four themes from the codes. This exercise was conducted twice, and, in both cases, similar themes emerged. Secondly, the suggestions for themes were combined and developed further to arrive at the final four themes proposed in this research. Thirdly, the recommendation from ChatGPT of how to split the codes between the themes was ignored. Instead, all codes were randomised again, and the researcher manually distributed them amongst the four themes applying the 4Rs framework proposed by Naeem et al. (2022): reciprocal, recognisable, responsive and resourceful. These three steps were adapted from the approaches suggested in recent studies by Morgan (2023), Zhang et al. (2023) and Zhang et al. (2023a) where ChatGPT was found to perform reasonably well when extracting abstract meaning from codes and keywords and can confidently be used as a supporting tool in the thematic analysis process at the stages of coding and theme development. The final themes were constructed; the themes and their codes are presented in Figure 4.2.

Theme 1 User Experience and Interaction	Theme 2 Information and functionality	Theme 3 Trust and Privacy	Theme 4 Emotional and Perceptual Aspects
Codes	Codes	Codes	Codes
page placement	Google equivalent	bots collecting data	frustration
rephrasing	Chat GPT equivalent	recommendations	annoyance
voice/speech	segmentation	ideas	giving up
transfer to human	specific Q & A	third party bot	surprise
avatar	complex Q & A	purpose of conversation	uncomfortable
bot vs search	free text vs options	privacy concerns	normal
personalisation	available 24/7	personal information	ease of use
order of preference	navigator	confusion	setting expectations
personal touch	negative impression/reputation damage	check the answers	personality
usefulness	speed/waiting	human-lived experiences	future use
navigating complex websites	accurate/relevant info		welcome message
navigating new websites	languages/translation		layout design
tone of voice	memory		
conversation flow	cost/headcount/productivity		
perfect bot	bot metrics		

Figure 4.2 Theme Construction from Codes (Source: Author, 2024)

Step five in the process is defined as “conceptualisation” through interpretation of the themes (Naeem et al., 2023, p.12). Concepts described as “emergent social patterns grounded in research” (Glaser, 2002, p.24) emerge from the analysis of the thematic networks that exist within the individual themes as well as the connections between codes classified in different themes. As the analysis moves from the specific to the general and from the practical to the theoretical, the concepts are linked and developed into a conceptual framework represented by a visual aid such as a diagram (Jackson and Mazzei, 2022). The process of conceptualisation led to two main outcomes. Firstly, the themes became more defined and accurate with the theme names augmented to more correctly represent the codes they contained. Secondly, the differentiation of the codes into two groups became evident and the classification into “direct” and “indirect” influence was articulated in each of the themes by considering the factors relating to each one. The thread of determining the “purpose” emerged as an overall thread that ran through all the themes. The overarching topic of “purpose” was examined from the vantage point of the university, which led to the “purpose of the chatbot”, and from the vantage point of the student, which led to the “purpose of the conversation”. A sample of early conceptualisation ideas of Theme 1 is presented in Figure 4.3.

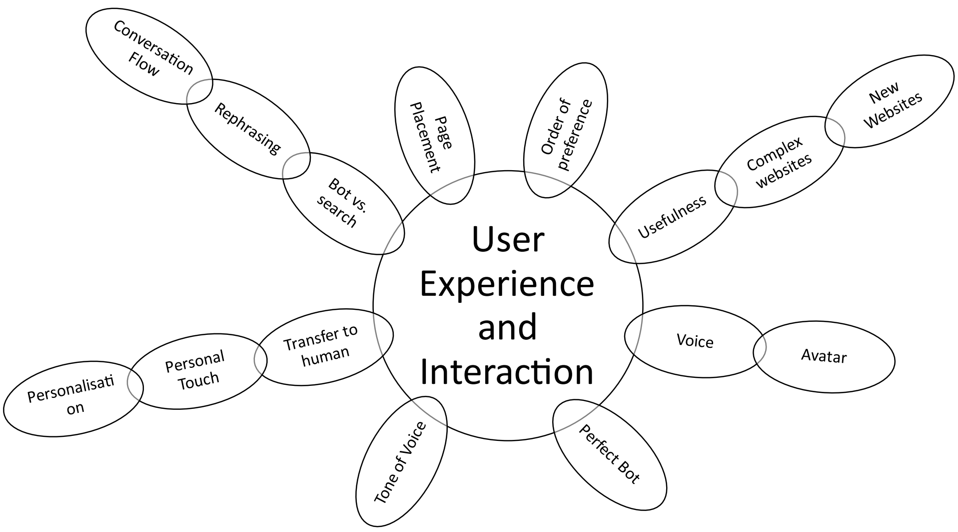

Figure 4.3 Early Conceptualisation of Theme 1 (Source: Author, 2024)

Step six is the final stage in this process where a conceptual framework emerges as a result of the rigorous and systematic application of the previous five steps. In this research, the conceptual framework was grounded in the research findings stemming from the empirical data and it comprehensively addressed the research questions. The theoretical framework, which combined ELM and UTAUT2, laid the foundation for the conceptualisation of the framework and provided a novel way to apply the two theories in the specific context of student recruitment in HE and to answer the research challenges posed by Puntoni et al. (2021) and Følstad et al.

(2021). Driven by the social constructionism paradigm, which lends itself to an inductive research approach, this framework was based on the themes that emerged from the empirical data and allowed for a novel approach to the exploration of the effects and benefits of CAs as part of the student journey.

4.3 Major Themes

4.3.1 Theme 1 – User Experience and Interaction

The first theme of User Experience and Interaction is defined as the perceptions and responses of users resulting from their use of, and interaction with, CAs. The associated codes and keywords identified in the analysis have been summarised in Table 4.6 below.

THEME	DEFINITION	CODES	KEYWORDS
User Experience and Interaction	The perception and responses of users resulting from the use and interaction with conversational agents	usefulness	• Useful • Some situations • Saved time • Interact • Refer to website • Links • Separate sections • Quite clear • Comes with me • Cover everything • Gave phone number to call • More detailed answers • No specific information • Give the thing you want • Multiple choice questions • Generate the right answer • Helpful • Connect to agent • Efficiency • Evolved
		navigating complex websites	• A lot of information • A lot of sections • Combine sources • Very hard to navigate website • Assistant • Directly to link • Navigate website easily
		navigating new websites	• Find things • New websites • Easier • Take you straight there • Students new to education • UG • Know how to use • New to education • More beneficial

		bot vs search	• Search function • Narrow down • Search myself • Additional steps • Some useful information • Continue search on website • Go back to chatbot • Should find all the information • Scroll • Not patient • Expecting support • Clearer • Taking its time
		rephrasing	• Rephrase • Keywords • Adapting my terminology • Narrow down words • Doesn't follow • Word the question • Doesn't understand
		conversation flow	• Having a conversation • Options killed the conversation • Ask questions • Not like a conversation • No conversation flow • Disregarded info • Individual question • Keywords • Doesn't customise • Open-ended questions • Not intuitive • Not emotionally intelligent • Back to the beginning • Repeating answers

			• Interpret everything
		transfer to human	• Nice feature • Given the opportunity • More human options • Pretty important • Real-life team • Always good to have the option • Important • Reassurance
		personal touch	• Personal touch • Additional info • Crisis • Mental health • Welfare concern • Impact on student experience • Person looking for interaction

		personalisation	• Dry • Personalisation • Using my name • GIF • High expectations • People like interaction • Ask question instead of search • Comforting • Different audiences • Different needs • Personalised website
		tone of voice	• Friendly • Joking • Interact • Tune of the conversation • Others more formal • Not give random options • Obvious it's a bot • No feeling • Welcoming • Exclamation marks • Silly • Cozier • Cringe • Trying to be cool • Not impressed • Professional • Not professional • Contradicts academic rigour • Casual • Cute • Irrelevant • Voice of the university

		voice	• Impractical • Read it again • Understand • Voice note • Accents • Pronunciation • Word the question
		avatar	• Different • More pleasant • Nice • Experience more real • Don't mind • Comfortable • Speaking to a human • Not a game • Interested in the info • Want complex outputs • Want speed • No need • Ok to be a robot • Mascot • Fun • Freak me out • It isn't human • Amazing • Exciting • Facial expressions • Humanity
		page placement	• Home page vs study page • Moves from tab to tab • Can't find the bot • Hidden behind cookies • Wasn't visible • Off-putting

		order of preference	• Depends on type of info • Simple info – chatbot • Specific info – human • Firstly website • Save time – choose the bot • Go to Google • Search myself • Chat first
		perfect bot	• Simple • Options plus free text • Links and information • Different languages • Reference whole website • Multiple sources • Save time • Talk to human • Use my name • Find out information • Engagement • Rephrase or explain • Interaction • More like ChatGPT • Humour • Accessible • Personalities • Not intrusive

Table 4.2. Theme 1 – User Experience and Interaction (Source: Author, 2024)

There are multitude of definitions on what constitutes the concept of "user experience" positioned within various domains of both theoretical frameworks and practical domains. For the purpose of this research, the understanding of user experience was derived from the "user-centred models" defined by Forlizzi and Battarbee (2004, p.262) as models that "help designers and developers to understand the people who will use their products". These models facilitated the path to understanding students' actions and aspects of their experiences that are relevant when interacting with university CAs. Based on this understanding of human-centred design of interactive systems, Følstad and Brandtzaeg (2020, p.2) proposed a definition of "user experience" in the context of chatbots to be "a person's perceptions and responses resulting from the use and/or anticipated use of a product, system or service". The perceived "usefulness" of a CA is central to the "user experience and interaction" theme as it captures a variety of views and beliefs about what should be the underlying purpose of engaging with a chatbot. Both ends of the spectrum were represented in the comments. For example, those on the positive end found the chatbots useful for the purposes of directing them to the relevant pages, providing links and saving time in comparison to searching by themselves. However, others were dissatisfied with the guidance provided and believed their own capabilities to search the websites independently were superior to those of the chatbot. One participant from the UG group highlighted an added benefit to using a CA when they were provided with additional information that they had not considered asking for:

> *"I've chatted with bots before and, in the past, actually, they haven't been very useful. I found today somehow useful to chat with the bot because they directed me to pages which contain information that I was looking for, and this saved me some time compared to just a general search of the website. Also, they provided me with some additional information, which maybe I wasn't considering as important for me, but when I was presented with these options, then I understood that maybe this kind of information would also be somehow useful for me and I should read it and get more familiar with it."*

Another participant from the same group commented specifically on the usefulness of being provided with links and phone numbers to call:

> *“I think they were more useful, because the company seemed to have put quite a lot of effort into their chatbots. The answers were more detailed than other ones’, and they gave me a phone number to call. I found it useful. A lot of the ones that I've used before didn't include links. So, it was quite useful that it took me straight to the place that it's needed on the website. As a whole it is quite clear.”*

This view was also shared by some of the participants in the PG group. One participant commented specifically on how easy it was to get to the right place on the website by following the multiple-choice questions provided:

> *“That bot gave me more multiple-choice questions. So, it's a bit like on the phone with “press one for this”, “press two for that”. And it was trying to direct me a little bit more, rather than the first question asking you to retype what it's about. And only then it starts to narrow down my choices and directing me. That was probably quite helpful, I think, because the questions I typed might not have generated the right answer, but at least I could follow a pathway with that.”*

This view was supported by some marketing professionals who were much more critical of the CAs’ performance, especially when they were asked to “put their marketing hat on”.

> *“They are way better than the one I used. I do think that now, with AI getting out there in everyday life, the technology has improved quite a lot, and bots are really, really becoming much more effective than the annoying thing that they used to be. If you do a proper keyword match to the right URL, I think it's*

very, very helpful for people; more than to spend time calling. Lots of simple questions can be sorted by the bot. It is no longer something that is useless."

However, these positive experiences were not shared across the board. In some cases, the bots were not able to consistently provide value or meet the expectations of the participant. In some cases, a genuine feeling of disappointment could be observed during the interaction. After interacting with the three CAs, a UG student commented:

"None of the three bots gave me the specific information that I wanted to get. But I think that all of them managed to navigate me to a place where I could find the information. But if I wanted to find all the information by using them, I wouldn't be able to do that."

Others had mixed experiences amongst the three bots they interacted with:

"I think the first one was the best because it had more direct answers and also understood the broader questions about animals and looked at the whole website. The other two I didn't find useful, I thought they didn't answer my questions. With the first one – definitely. It didn't feel like I was talking to someone but still felt like I was getting help, and I felt like it was getting what I am doing. For the other two, again, more like a robot and just saying any information that might be related."

The majority of marketing professionals were quite dissatisfied with the experience and found the bots "not sophisticated enough", "frustrating", "useless", "scary" and "annoying". One marketing professional summarised their negative impressions as:

"This is not a good user experience at all, because the flow of the questions and responses is not really what I'm after. They've not really answered my question. They directed me to an online perspective to sift and search for the

information. I could have done that myself by looking at the website. They've not really helped with my enquiry. I would say that this is not a good chatbot at all. I think this will probably end up frustrating a lot of students."

The positive views of usefulness indicated that bots are a preferred channel of communication for the students, especially the ones from the UG group. One participant recalled a frustrating experience trying to find information on the MIT website, and failing, while wishing there was a chatbot to help them navigate the complex web of pages, sections and information:

> *"For example, MIT, I want to try to go there. … I've searched for more specific information, like what requirements do they have, what [programme] is good to do. These answers were in their blog. I found their website very hard to navigate through. Asking the chatbot, helped me a lot."*

Another UG student confirmed:

> *"I think universities should invest in bots, because the websites have a lot of information on them. And whilst they do have a lot of sections, sometimes it can be a lot more convenient if you can just search for the answer, and it will take you directly to the link. I've been on university websites before, where I can't find a specific bit of information. So, I think they should invest in chatbots and make them have detailed answers."*

Marketing professionals admit that sometimes they create websites that are indeed complex and contain a lot of information. However, a well-designed website should not need a chatbot to help a user navigate. These two opposing views are captured here:

> *"The bot is a good way to navigate the information on your website, because there's a lot of information, particularly when it comes to courses, admissions*

criteria, accommodation, fees, funding, visa. They can't find that information easily on your website, because it's too big and the navigation or the sitemap isn't clear enough."

versus,

"If you can navigate the website easily, you shouldn't need a chatbot. So, if that chatbot is being used for the user journey, then there is something wrong with the website. I feel a website should be easy enough to navigate however many pages, the UX [user experience] of the site, you don't need a chatbot to navigate the site."

Related to this point was a comment from a 17-year-old participant regarding user experience when visiting a new website for the first time:

"I think it would make websites easier to use as well, especially when it is a new website and you've never used it before. If I went to a new website that I haven't been to before, and I don't know the structure of the website, rather than going and trying to find the structure and how things work, I would prefer to have the bot take me straight to the place I want to go."

This aspect of usefulness for typical 17–18-year-olds was also recognised by the marketing managers responsible for launching and maintaining bots:

"I think that possibly the typical 18-year-old wants information so quickly that they may not necessarily be willing to even navigate a couple of pages into a website. I could be wrong. And that's where you've got the opportunities, in the way that Solent has done, to possibly drop a couple of marketing messages and categorise things that are a bit more, more top level to begin with."

The remaining codes were grouped into two distinct categories according to Hassenzahl's (2018) framework for user experiences and divided into "pragmatic" and "hedonic" attributes of an interactive system. Pragmatic attributes relate to instrumental characteristics that determine whether the bots provide task-oriented functionality in a user-friendly manner. Codes under this category are bot vs search, page placement, rephrasing, voice, avatar and transfer to human. Hedonic attributes relate to how the communication and interaction aspect of the user experience is perceived on a mental and emotional level. Codes under this category are the tone of voice, conversation flow, personalisation, personal touch, order of preference and the perfect bot.

Historically, a search for information was a very manual and labour-intensive task that many people either enjoyed immensely, because of the sense of discovery it brought, or disliked immensely, because of the tediousness of going down rabbit holes and not really finding the information they had set out to find. Bots have the potential to make this process more pleasant, however, many of the participants realised that the bots were not sufficiently developed to carry out the entire process and they reverted back to the more traditional approach of searching by themselves.

A UG student observed:

> *"We are searching for information but not using the bot. We're just using the search function of the website, because the bot didn't take us that far. What the bot has done is taken me to this page where, in the search field, I can narrow down the available courses to the topic that I am interested in. But I did the search myself. The bot didn't tell me whether they have it or not. I had to do additional steps to get to that information."*

A similar view was expressed by another UG student:

“It's taking me to a course search page. So, basically I’m doing the search myself. I am not using the bot's help anymore. I would usually switch to finding information myself, because if I was to click on the course that I was interested in, they will probably have everything on there. But then, once I wanted to look at something else, let's say if I wanted to look at funding, then I would go back to the chatbot.”

The second statement confirms the participant’s intention to switch between the bot and the self-searching approach until they find all the information they are looking for. The feeling of impatience with the ability of the bot to provide all the necessary information was expressed even stronger by the PG group of students:

“I didn't find the bot very useful because this information I could have found on my own just searching on the website. They do provide options and links to the options, but the options are so many that basically I could have just gone through the website; it would have been the same to me at least.”

and:

“And if I would love to continue with this chat, let's say I want to find a course. But I would find this page by myself with one click on the main website with ‘All courses’ here. Postgraduate courses. This is effective in a way, you don't type things, you choose things, but it's not efficient for everyone.”

Triangulating these opinions with the views expressed by the marketing managers revealed that the approaches of even some of the most experienced professionals in the field were similar to those of students; the marketing managers thought, “Let me have a look myself” when the bot was taking its time to produce an answer or “I could have found that information fairly easily myself” when the bot failed to provide a link to the information displayed. One marketing professional went as far as to admit that search functions on websites are sometimes inadequate:

> *“Sometimes, search functions on websites don't work very well. I still think that bot wise, it's a combination of things. You can ask a question and then they give you a short answer and also provide you with the link. So, it's a bit different from a search function, and not all search functions work very well.”*

Part of the reason why participants chose to switch from using a bot to the search function was the additional effort some conversations required when the bot didn’t provide a satisfactory answer; for example, a participant decided to rephrase their question using words they believed were more attuned to the bot’s capabilities to decipher surface and hidden meaning. Some participants rephrased their question from specific to more general, whereas others reduced the complexity of their question by changing a full sentence to just keywords. Some went as far as to assert that speaking to bots requires specific skills and a “special language”:

> *“I found that I had to just keep changing things, change my keywords to really tailor down the information that I need. I felt like I had to narrow my words down to just keywords. I noticed that rather than using phrases like ‘PhD in Business Management in management’, I firstly had to throw in keywords like ‘postgraduate’, which then threw in master’s courses. I then had to throw in keywords such as ‘postgraduate research’, and once it recognised the courses I'm looking for, I then had to further narrow down my search and type in ‘PhD in Business Management’, and that's exactly when it was able to pick up exactly what I needed. So, I can see the difference in adapting my terminology and the words that I'm using.”*

In one of the interviews the bot requested the participant to rephrase the question, which left them a little despondent and unsure what to do next:

> *"I had to rephrase after copy and paste did not work. Bot asks, 'No problem. Please can you rephrase your question'. Yes, not really helpful. So, whatever I rephrase it to I feel that I'm not getting it. I'm not asking a very long question. So, there's no conflict there. Okay, at least they tried."*

The "pragmatic" issue of rephrasing represents an aspect of the more "hedonic" attribute of good or bad conversation flow. When a participant has to rephrase they might perceive the conversation as not resembling a conversation with another human being. When an information exchange has a good conversation flow, then it goes some way towards a user feeling satisfaction with the experience of using a chatbot to gather information. For example, one UG student observed:

> *"At the beginning it felt like we were having a conversation, then within the course of the conversation those options which were presented killed the conversation, just because the chatbot could have asked about more specific information related to my search and then, maybe, direct me to a link and not just give me some random options to pick from."*

Another feature of a good conversation flow that seems to be missing in these experiences is to build the conversation from one question to the next. A participant from the PG group noticed the bot providing the same answer twice at the start and further on in the conversation, which may have even convinced her to stop interacting and seek human help:

> *"Yeah, it's repeated. It's asking again, so it's not keeping up with the conversation. It's just all very, very automated, not intuitive or emotionally intelligent. It's taking me back to the beginning of the conversation. This is*

useless really, isn't it? It's not very helpful. I'd rather speak to a person. It would make me want to speak to a person. I'm one for more chat, message, text, email, over a phone call. But it would make me want to pick up the phone and get what I need."

Marketing professionals recognise this as an issue and the frustration that a lack of conversation flow can cause, especially when more and more people are exposed to the easy conversational style of generative AI tools such as ChatGPT:

"The disadvantage is if the bot is not answering the question and is always giving the same answer. It can really anger people, not giving the quality back."

and

"I do like the conversational style of ChatGPT. It does give me the feeling that I'm conversing with somebody, I'm having that kind of element of human interaction in some way because it's so conversational."

When the conversation flow failed to satisfy participants or the information provided was not accurate or relevant enough, the participants often looked for an option to end the interaction and be given the opportunity to ask their questions to a human. This option was not always available or it was not always obvious how to access it. The UG and PG students were unanimous that this option must always be offered and be easily accessible. Some of the participants said:

"I think a nice feature may be that you're always given an opportunity to be transferred to a human being if the bot is struggling. Especially for more personal questions, I think that the human option is definitely good."

and

> *"If you can't get the answer you want within like two or three questions, they should not have an infinite loop but should say, 'We'll put you through somebody'. Even if I was doing it in the middle of the night, and I got to a point I can't find out what I want, if there was an option there like, 'We're going to send your transcript through to somebody and they'll give you an email back in the morning', I'd be delighted to be able to actually talk with a person at some point and get whatever it was that you couldn't get across to the chatbot."*

However, the marketing professionals did not see the issue so black and white and had somewhat nuanced opinions on when it would be appropriate to involve human agents in the conversation. Some fully agreed with the students' opinion of 100% availability of the option:

> *"I think it would be good to always have the option to go to the enquiry form or to go to a human straightaway. That would be ideal. I do believe that a bot should always end up with a live agent. But then if the bot becomes so good that you don't need the live agent then we are in trouble."*

Others considered the lack of this option to be a result of the university's marketing communication strategy not to invest in agents or apportion time to repetitive questions that the bot should be able to answer:

> *"They don't have an option of 'I would like to speak to an agent'. I guess because they don't want you to speak to an agent. They don't want their agent losing time here. Again, commercial strategy. It all comes down to what the board wants. Do you want to have specific agents investing their time here? Yes or no? Or do you want not to invest in that extra headcount and let the student do the job for you."*

and

> *"I think if I had that option, I would have already contacted a human the minute I didn't get the answer I was looking for. If there's an option where the bot offers to put you in touch with the university directly during the conversation, then I think everybody will end up using that and it makes the bot a bit redundant."*

The desire to speak to a human was also sometimes driven by the experience, which was described as lacking a "personal touch". Participants described bots as "lacking in emotional intelligence and human touch" or not being able to assess their impact on "mental health". Returning to the recurring thread of purpose in having conversations with bots one participant pondered:

> *"I can imagine a person who was looking for some conversation and not getting this conversation, and not getting the information, actually being more frustrated in the end, than their experience without any chatbot options on the website. So, maybe, yeah, if you're the type of person who really relied on speaking with somebody and getting information that way, and not getting it, getting a bit frustrated there."*

The value of a personal touch that is not currently captured by bots may be the ability to offer additional information that the student did not think or know to ask about, which would happen naturally during a human-to-human conversation:

> *"Maybe the disadvantage is that the personal touch is missing and the chatbot is providing me only with information connected to the wording that I use and is not able to provide additional information, unless you're specifically asking it for this information."*

This kind of proactivity to volunteer information that has not been explicitly asked for is considered the seed of personalisation and is seen as very valuable by both students and marketing professionals. Personalisation can mean different things to different people. Some liked being addressed by their name, whereas others enjoyed the little personal touch offered by one university in the form of a “cat” GIF waving to welcome the participant. Here are some of the observations captured in the statements:

> *“Yes, they could have literally said, ‘Hey, Jane, what do you want to do now?’ Rather than just that generic question because that makes me feel like they know it's still me and I'm still talking to this person. But after the cat emoji it got lost and it didn't happen again. So that might be nice to make it a little bit more personable.”*

and

> *“I think it's important to personalise things quite early on. I did really like this style, ‘Oh, what's your name?’ and then we'll call you by your first name.”*

One marketing manager offered a solution of how the bot can be made to appear more personable by picking up some key information on the person interacting with them:

> *“Ideally, it will be able to show me whereabouts regionally the question is coming from so that answers can be tailored accordingly without having to ask some of those questions. Would it be able to tell me where the individual had already been looking on the website? For instance, if the individual had been looking around the business faculty page, rather than asking them what courses they're interested in, start with that.”*

Whether the bot appeared to mimic “personal touch” or managed to achieve a level of “personalisation”, the driving factor in the success of many of the conversations observed was the chatbot’s perceived “tone of voice”, which was also described as a “hedonic” attribute of the interaction. Almost every participant made an observation about the bots’ tone of voice, even in the instances where they were claiming that all they wanted was accurate and relevant information and then nothing further. It was interesting and some of them were challenged to explain why tone of voice would be important if all they wanted was substance. It seems that in the students’ communication with a bot both the central route and the peripheral route, as described in the ELM, are employed. The students apply focused, cognitive efforts to obtain the relevant information from the bot and notice context-based, heuristic cues, such as tone of voice, to determine whether they should accept the information offered. Examples of this duality can be found in these statements:

> *“I think it was friendly and joking but it still was very simple and to the point, so it didn't distract me in any way.”*

and

> *“The third one yes, absolutely. 100% friendly. The first two, I wouldn't call them friendly. More professional. Bit more serious and straight to the point there.”*

and

> *“I think that the chatbot is meant to be the voice of the university. It's meant to be that person that you're talking to. If it's not actually going to be a real human, they still got to be welcoming and wanting you to come. The fact that the little chatbot said, ‘Oh, you've made a great choice. Nice to meet you. Amazing. We're sure you're going to love what we have to offer’. That's*

> *exactly what a human would say. It's like a saying, ‘We have pride in our products’ and ‘We're not scared of you’. It comes across well.”*

One of the bots used in the task-based part of the interviews had a distinctly different and friendlier tone of voice than the others. The importance of striking the right tone with the students was summarised by a marketing manager as follows:

> *“This tells me that this university, their vision and their mission and their branding guidelines, their tone of voice is very personal. I guess it is within their branding to be amicable, personal, youthful. I'm just getting all these things just from the way they communicate. So, I can tell if I am a student that likes or empathises with that kind of culture, that this university would be, ‘Yes, oh my God, this is so me. I'm definitely going there. I am liking this brand already’. However, if you do not feel that this is in line with what you see yourself as into, maybe you are a more serious person, this person will be like, ‘You know what, from the get-go, I don't think this is for me’.”*

Returning to more “pragmatic” attributes, the participants were asked to imagine various scenarios where the bots had features or capabilities that are not yet evident in university bots. For example, participants were asked their opinions on the ability to communicate with bots via voice – both from the side of the participant where the student can ask their questions via voice in a similar manner to Siri and Alexa, as well as from the bot’s side where the bot would reply with a voice response rather than text. The perspectives on using speech to communicate with chatbots highlighted a range of considerations including accessibility, privacy concerns, environmental factors and individual preferences. Some participants recognised the benefits for students with mobility issues who might find it challenging to type; thus, they underscored the importance of inclusivity and providing alternative methods of communication. Another view on the topic of accessibility was:

> *“It depends, maybe a bit more human characteristics, but it should have an option if you want to hear the messages they send you or not. For the visually impaired students maybe it's better.”*

Surprisingly, a 17-year-old participant absolutely refused to speak to bots giving the following reasons:

> *“No, I don't think I would want to speak to a bot. In our day-to-day life, we text to other people. I don't send voice messages that regularly. It would be way easier to get a text back as an answer. I don't think that many people use their microphones to ask questions. And I also don't think that many people would like that, because people are very scared and concerned about their privacy and they would think, ‘If I send my voice here, they could use it’.”*

Another 17-year-old participant was of the same opinion but for completely different reasons:

> *“If I was able to speak to the chatbot and the chatbot spoke back to me, I would not use that option. I think it's a little bit impractical. If I'm somewhere in public, I wouldn't just speak with a chatbot. When you have it on text, you can just come back and read it again if you need it or read it a few times if you don't understand it. And if it's speaking to you, you can't get to that information again.”*

The objection described in the above quote about the lack of record of what was said may be overcome by one participant’s suggestion for a better bot experience:

"Maybe you can get a PDF of your responses and then you can have it. Sometimes people send themselves a document they can look at later and save for future reference."

Marketers speculated on other environmental factors that can make voice communication challenging:

"The other way of looking at this is, What environment are the students in when they are looking at the website? Have they got headphones on? Are they on a train? Are they at home? Are they in an office? Are they somewhere where dialogue maybe banned? They can't talk openly in some places, whereas you can have a discreet conversation with typing."

As well as voice, the participants were also asked to imagine a bot being represented by an avatar with predetermined appearance features, such as face, hair, eye colour, skin colour, voice tone and so on. The perspectives on this topic were diverse and extreme with some participants expressing real enthusiasm at the prospect of humanising the bots, others were not bothered and some said that they may detract from the credibility of the bot to the extent that one marketing professional labelled them "gimmicky". Below are some of the words used by one UG, one PG and one marketing professional participant to express their views:

"I want to use the bot to find out answers about the university that I want to go to. I'm not playing a game. I don't want it to jump and say something or do something. I want to get the specific answer as fast as I can. So no, I think that people should not waste their time to develop those kinds of features and probably they should spend time on making the chatbots able to do more and to produce more complex outputs."

and

> *"Yes, an avatar would be amazing. What would be quite good to have is if, for example, the customer that that you're there speaking to, if they're able to put in some key information about themselves, and they're able to create an avatar or an emoji that looks like the customer. I think sometimes when you're using the app or using these bots on an app, or whether it's on a web page, you quite often find that it can be quite boring, and it's not very user friendly. But I think having the avatar would make it a bit more exciting, but also make it a bit more real, especially if there's a voice behind it."*

and

> *"I think it definitely adds another element of innovation to the chatbots, for sure. I think we probably need to strike the balance of whether it comes across gimmicky or whether it's actually going to add value to the actual interaction that the enquirer is going to have with the chatbot. You want it to come across as credible and I think some of the things that I've seen with some of the chatbot features that are available out there, my personal opinion is that some of it does look quite gimmicky."*

Another aspect of the user experience that was tested in the interviews was the availability of the bot either in the home page or in one of the more internal pages such as the "Study" page. This is not an attribute that the students viewed as very important to them, even though their preference would have been for the bot to not only be available at the start of the information search, but also to stay with them and move from tab to tab as the search progressed. The marketing professionals attempted to hypothesise why the decision may have been taken not to have the bot always available from the start. One marketeer guessed:

> *"Wow, that's weird. I don't think this is a good choice. No, as a marketeer, you want your level of communication to be available all the time. That's what you expect. Although, I do see potentially why they have done it with 'Study'. And I think they have done it with the 'Study' page so that they don't get enquiries about something else that is not related to the course of promotion."*

Another marketing manager elaborated on the same issue:

> *"I think if someone wants to use them, I think it's better that they are visible. I would make it available and if someone doesn't want to use them, they don't. They will just ignore it. I think it's best to have it because sometimes people if they don't see it straight away, they just want to go to another website, if they don't have instant contentment."*

If we consider the above "pragmatic" attributes internal to the functionality and design of the bots, one external factor that determined the quality of the user experience was the participant's choice of when to use a bot and when to use other methods for collecting information. The participants were asked the order in which they would ordinarily use the available tools to collect data: the website, the bot, email or phone, Google Search. The interesting discovery from that question was that the bots were never the first port of call and choice for interaction, but they were also never bottom of the list. Most participants said that they would turn to bots for help either as their second or third option for information search channel and, in many cases, they preferred interacting with a bot to speaking with a human being, especially representatives of Generation Z regardless of whether they were looking for a UG or PG programme. A common pattern was for participants to start with the website and then either try the bot or turn to humans for help. Here are some examples:

“I'll firstly, probably search on the website, because that's what I'm used to. I don't usually use chatbots that much. If I find it way too complex or I couldn't navigate or I couldn't find the answer that I needed, I would then ask the chatbot and thirdly, I will call the university maybe.”

and

“If I don't know much about a topic and I'm trying to gather information, I may go to places like ChatGPT and Google. But if I do have an idea and my question is narrow and targeted, I will go straight to the website. I'm not going to use any search function. Google Search will be first, website search will be second. Most of the time when I go to the website, I ignore the chatbot.”

To complete the theme of user experience, the topic of what makes the perfect bot revealed diverse expectations that emphasised the need for simplicity, versatility, personalisation and effective communication. It should provide a seamless experience, take into consideration users’ preferences and offer a balance between structured options and freedom in the interactions. To illustrate some of these views here are some recommendations to designers of what might constitute the perfect bot in terms of pragmatic attributes: “keep it simple”, “combination of links and information”, “give specific information”, “provide ideas”, “use multiple sources”, “remember me”, “different languages”, “freely ask a question” and “transfer to a human”. The hedonic attributes that participants highlighted were: “personalisation”, “use my name”, “straightforward”, “save me time”, “be curious about me”, “less robotic” and “more engagement and interaction”.

One sceptical PG student summarised their views as follows:

“Doing his job properly! Like being friendly when you're typing, like giving you suggestions, ideas, like sometimes self-corrections that you have when you're

typing on the phone or in any apps. Or at least ignoring or for example finding the closest to what you're typing. Then I expect the chatbot to ask me, 'Do you mean this? Do mean that?' So, it's somehow helping me to clarify the point like Google does. Instead of just telling me, 'Sorry, I don't understand you. I can't help you'. Not right away disappointing you."

When this question was posed to the marketing professionals, they valued a different set of capabilities and looked at the bots from the university perspective, for example, capabilities that would make a perfect bot from the point of view of the organisations developing and launching them. The attributes that emerged were "mapped well to keywords", "give links to enquirer", "lead generation and qualification", "easily accessible information", "good conversation style", "follows generative AI", "good logic structure", "integration with CRM", "human handoff" and "email record of the chat".

A marketing professional summarised their views on the importance of testing for user experience:

"There's two ways of coming at this. The first is the university's perspective. Who are we, what's our mission, our values and what we stand for? I would expect to see my university to be very compliant, and ethical, and dignified and mature. The other perspective is, how are we attracting the students? What would they see as valuable and useful? And how do they feel they should be spoken to as well? And that's why user experience testing is absolutely critical. So, no matter what the technology is, you have to put it in front of real genuine students and go, 'Does this work for you?'"

When asking the participants about the perfect bot, there was a wide consensus that the third one came quite close to their idea of "perfect". The interesting aspect of this view was that this bot was the one with the most limited functionality and simplest interface. A marketing professional described the third bot as follows:

"I am not going to lie; I really like the third bot that we looked at. And I think after our interaction, I'm probably going to revisit that one again and look at the way it's been built, because I think they are probably spot on."

One of the UG students was also of the same opinion:

"Maybe the X University chatbot with the GIFs and personalisation was the closest to perfect, maybe to add on the ability to freely ask a question. But honestly, the X university chatbot was amazing!"

The next theme explores the various aspects of functionality and usability that some of the topics above alluded to.

4.3.2 Theme 2 – Functionality and Usability

The second theme of Functionality and Usability is defined as the specific attributes and characteristics of the CA that allow users to achieve their goal in a "question-answering" interaction. The associated codes and keywords identified in the analysis have been summarised in Table 4.4 below.

THEME	DEFINITION	CODES	KEYWORDS
Functionality and Usability	The specific attributes and characteristics that allow users to achieve their goal in a "question-answering" interaction	accurate/relevant info	• Not of interest • Doesn't exist • Precise • Understands • Helpful • Normal to give wrong information • Pinch of salt • Relevant info • Correct information • Offer alternatives

		specific question and answer	• No specific answers • Just sent to blog posts • Direct questions • Agent • Sent round the houses • General information • More precise results • Sort in categories • Needs to speed things up • Not answering well
		complex question and answer	• Several words • Complicated questions • Not random info • Didn't pick up • Don't ask one question at a time • Keywords • Complex queries • Awkward questions
		memory	• Remember • New conversation • Longer conversation • Enter data again • Convenient • Connect • Elaboration • Archive previous answers • Individual questions • Amnesia • Forgot who I was • Didn't pick up • Didn't go logically • Doesn't follow up • Valued • Authentic

		ChatGPT equivalent	• Conversation flowing • Understands • University bots more personal • Appropriate • String together • Specific information • Wrong information • Short answer with link •Summarising • Like speaking to real person • Personable
		Google equivalent	• Spelling • Use to search site • Extended • Detailed • Specialised • Keywords • Most relevant pages • Better than web search
		navigator	• Beginning • Show me • Options • Navigate • Some directions • Starting point • Basic guidelines • Source of information • Guidance • Continue myself • Streamline
		available 24/7	• 24/7 • Any time of day or night • Quicker • no need to queue • Evening • No specific timeframe • Working hours • All the time • Peak curiosity

		speed/waiting	• No waiting • Not stuck in a queue • Passed around for answers • One place for all info • Efficient • Easily go through • Make admissions quicker • Immediate replies
		free text vs options	• Don't understand • Happy with options • Option to type • Helpful • Engaging • Simpler • Very guided • Tailored • Specific answer • Like clicking • Less typing • Less chat • Good categories • Making me tired • Ask my question first
		languages/translation	• Personal • Parents • Helping • Important • Cool • Positive • Inclusion option • Really useful
		segmentation	• Younger audience • What stage • Gain more info • Location • Visited before • Target audience • Filtering enquiries
		negative impression/ reputation damage	• Damage of reputation • Loss of trust • Will not use

			• Worry • Worse • Challenging • Should work • Less likely to apply • Put off student • Think less of uni • Damages brand value • Influence your opinion • Perception • First impression
		cost/headcount/productivity	• Expensive • Staffing costs • Efficiency • Better productivity • Invest in headcount • Quality interaction
		bot metrics	• Drop off rate • Sentiment analysis • Need to rephrase • Increase dwell time • Reporting functionality • Quantitative metrics • Qualitative metrics • Conversion rate • Applications • Students

Table 4.4 Theme 2 – Functionality and Usability (Source: Author, 2024)

The theme of “Functionality and Usability” links back to the definition of what CAs are and expectations of their performance. According to Gao, Galley and Li (2019), CAs are question-answering models that are designed to generate concise and specific answers to users’ questions. Hassenzahl (2018) specifically linked the pragmatic attributes of an interactive system with the “task-oriented” functionalities that provide usability in an accessible and easy-to-use manner. However, a distinction should be made between functionality and usability, even though computer designers often equate the two concepts or sometimes view usability as a limiting factor of functionality. Broadly speaking, the functionality of a system can be defined as “the functions a user needs to accomplish a task or set of tasks” (Goodwin, 1987, p.229). Goodwin added the clarification that “the effective functionality of a system depends on its usability” (Goodwin, 1987, p.229). Therefore, users are most likely to select a system that provides functions needed to perform specific tasks, which links back to the notion of purpose. Students will choose a channel that is most useful in performing the task of providing information on courses.

The functionality that scored highest on the participants’ list of expectations was for the bots to be able to provide accurate and relevant information. There are two distinct types of concerns with the bots’ performance on this aspect of functionality. One aspect was that the information provided by the bot was simply going to be wrong. This was a surprise for some participants as they assumed that the database that the bot was utilising to generate answers would provide the same information as the website, which they assumed to be correct. The other concern was the expectation that the bot was likely to provide irrelevant information and they should do further checks to confirm the information themselves.

Here are two distinct views from UG students who were indeed served wrong information while interacting with the bots during the interview:

> *“I've used chatbots before and it's normal for them to output even wrong information and sometimes they produce very wrong information. And I take everything that the chatbot says with a pinch of salt.”*

and

> *"Getting the correct information, regardless of how you get there, it's the most important thing. I'd say the main reason to go to speak to a chatbot is to gain the correct information, not so much if it's a pleasant conversation."*

Even though the chatbots occasionally served the wrong information, they served information that was not relevant or did not have a connection to the question being asked more often than they delivered incorrect information. Almost every participant had a version of the experience where they asked a free-typed question, and the answer was completely irrelevant to the question. Here are some of their reactions:

> *"So, they've come back with four articles. First one about A levels – not relevant. That's not relevant if I've asked about postgraduate. Second one about studying medicine – not relevant. Third one about A levels again – no, not relevant. Fourth one about transferring between courses – not relevant. Basically, this bot just gives you pages and articles that it thinks may be relevant but doesn't really give you an answer."*

and

> *"I know they won't give me the relevant information, they just send me off to another site that will send me to another site, and it is just getting more difficult to understand where I am, to search, to find and so on."*

The marketing professionals recognised the importance of this point and the priority to design a bot that has good keyword match in order to improve the relevance of the answers presented. This is how one marketing professional explained it:

> *"I think there's a little way to go with these bots at the moment to make sure that the information they present is exactly what's required straightaway. We've seen just very generic information presented to us, but I think as the AI*

becomes more sophisticated that will come and that's important because students of today expect information to be there at their fingertips immediately."

The functionality of bots providing accurate and relevant information is linked to their ability to understand very specific questions and then generate equally specific answers. Linking back to the topic of order of preference when searching for information, it would appear that most users would arrive at the bot with some knowledge and information already and would be using the bot to try to further refine their understanding of what their choices are. Unfortunately, most of the bots experienced in these interviews failed to provide this more specific information and reverted back to more generic answers that can be found on the website pages. Here are some comments of disappointment from the participants:

> *"It will be good if they gave the specific information, it would be much easier. I believe that chatbots are very helpful in that way, like filtering information and searching for information for you, rather than you going and searching for it. If I could ask a question and they will give me a full specific answer, and maybe reference where on the website they got the information from, but as far as I can see, most of them work as a navigator."*

and

> *"It needs to be really specific because otherwise I might as well just Google it myself. The chatbot needs to speed things up."*

Some suggestions provided by the participants on how to improve this particular skill was for the bot to: "sort you into different categories" by asking you additional "intelligent" questions; "taking the keywords and constructing the next bubble of text";

“use multiple sources”; and “reference some blog posts” was suggested as a way of providing a richer database that the bot can use to generate answers. This is how one PG student described the desired sequence of events to reach the desired goal of a specific answer:

> *“Once you've asked the question, you expect AI to ask you additional clarifying questions in order to give you a more targeted answer, like with human interaction. When you talk to your friend, how you know that he really listens to you is because he picks up the keywords and then he asks you even more personalised questions. Doesn't ask you generalised questions, because you expect that person is your friend and will be asking you intelligent questions about your life. And here, we don't obviously expect having super-intelligent questions, but at least taking the keywords and constructing the next bubble of text based on that.”*

A step up from being able to handle very specific questions was suggested by participants: the ability to handle complex questions when the user has typed a question containing two or more keywords that may require a complex answer made of several parts. This feature is currently not available in the university chatbots on the market, however, it is a feature that the participants are familiar with having interacted with ChatGPT since the beginning of 2023. A UG participant observed:

> *“I would like to see that chatbots can pick up several words from the questions at the time and be able to actually understand more complicated questions. Just because the question that we asked contains one keyword, which most of the time chatbots are able to pick up correctly.”*

A PG participant expressed a similar sentiment:

> *“If I was ringing up somebody on the phone, I’d probably preface it with, ‘I'm looking to do a course in blah blah, and I'm interested in the prices. But I'm also looking for… So, tell them all of your information’. You don't ask one question at a time, whereas with a chatbot you have to. If I typed in all of that in one go, they would probably give me so much information all at once, whereas a human would be like, ‘Okay, let's start at the beginning’ and go a bit more in order.”*

A marketing professional explained that the lack of skill to handle complex questions may be connected to another shortfall bots usually have, which is the capacity to link a series of questions together:

> *“That is a very difficult thing, to ask a complex question. If they don't remember what I wrote the first time, then it's all lost, because it's all single enquiries. It's a bit difficult to arrive at a complex answer if you always have to start from scratch.”*

Both the skill of answering specific questions and the skill to handle complex questions are reliant on a third capability and that is for the bot to have a “memory”. This appears to be a key factor when looking to improve the accuracy, complexity and specificity of the answers. Retaining the context throughout a conversation is a skill first demonstrated by ChatGPT and its equivalents. The users do not have to repeat key information to continue with the conversation flow but trust in the bot’s ability to understand that each question somehow relates to the previous one and the general topic being discussed.

Participants from all three groups unanimously agreed that retaining context and conversation history is a feature that will greatly enhance the usability of the chatbots and make the interaction not just functionally superior but also more satisfying.

UG participant:

> *"I think that it would be better if the university chatbots had some of the ChatGPT functionality, for example, to remember the previous question and to string everything into a conversation, because sometimes, questions need a bit more elaboration."*

And PG participant:

> *"It would be a nice feature to add where the conversation remembers previous questions in order to tailor the next one. I suppose you'd feel a bit more valued and also that it's a bit more authentic in terms of the conversation."*

And Marketing Professional:

> *"No, they've forgotten that I asked about undergraduate, because my question went from being specifically undergraduate to now 'list your marketing courses'. There's no sense that this chatbot understands what happened earlier in the process. It's looking at the latest thing. Its extemporising in the moment, rather than thinking of building a narrative."*

In many of the interviews, ChatGPT and other generative AI tools, such as Claude and Google's Gemini, were provided as an example of best practice, and specifically their ability to maintain conversation flow, remember previous questions and context, reply with a friendly tone of voice, have a hint of personality features and the ability to synthesise detailed information from diverse sources. The attributes quoted as desirable were the ability to: provide “links directly to the page of the course that I want”, “outputting information that is specific to my question”, “feels like you are having more of a conversation” and “summarising the information for you and giving you a chance to read more if you're interested”. A PG student went as far as to say that when interacting with generative AI it almost feels like you are talking to a human:

> *“I can clearly see that ChatGPT is far more advanced than some of the other bots that we looked at. And I think I quite liked that it was quite personable as well. So, when I put my name in there, it recognised my name and then the conversation just kept flowing. And it feels like you're talking to someone behind the screen and there is a real person there, as opposed to it's an automated system.”*

What generative AI also does very well is to provide alternatives and additional options that the user may have not thought to ask. UG participants recommended that the prompting of ideas would be a very desirable feature for the development of university chatbots:

> *“So, it gives me extra options that I didn't ask for. I think that's nice because sometimes you forget to ask and to search for those kinds of things.”*

In some cases, Google Search was also found to have superior functionality over the chatbots as well as the search function found within websites. This was particularly evident in Google’s ability to oversee and correct typing and spelling mistakes and still be able to decipher the meaning of the question being asked as expressed by this PG participant:

“If you typed in Google, Google would have spellchecked on your words. But this bot isn't really picking up a spelling error, which is different.”

and

“To be honest, this probably sounds ridiculous, but I usually just Google, like here, and then search through. All you ask Google is, ‘HRM MSc university X’ if I wanted to find out. I've had specific recommendations from lecturers, I know the good places. So, I know where I want to go.”

and

“Sometimes, I use Google to search the websites better than the search button in the websites.”

Some participants clearly indicated that Google was still their first point of information search, even prior to the university website. Google’s AI tool was also tested during one of the interviews; it provided concise and targeted answers that were followed by a link indicating where the information came from and where the student can go to read more if they were interested.

The participants’ comparisons between university bots, ChatGPT and Google led many of them to spontaneously label the bots as “navigators”. This term describes the current capability of the bots to lead the user to the correct place where they can find the information they are looking for, rather than to provide it themselves in a summarised form. Some users had exactly that expectation in advance of interacting with the university bots, whereas others were surprised that the functionality stopped there; they were hoping that the bot would take them further by providing the information on its interface rather than ask them to continue their search on the website pages. Usability of such navigators was perceived to be greatly dependent on how easy the website was to navigate manually. A UG participant described the following scenario:

> *"For bots like this, let's reference them as navigator bots, if the websites are well structured, I don't think that you need those kinds of bots. But I do think that bots in general are very useful if they could produce specific information. If I wanted to ask, 'What do I learn in computer science in this course?' and it lists me all the things that I'll learn, it would be more helpful. Otherwise, I would have to go on the page of the course, I would have to find it, I would have to read through everything to understand what I need to know. And if a bot could output that information, and give me the specific answer, I think that they will be very useful."*

One PG student observed with disappointment:

> *"So, it signposts. It's not very intuitive because it didn't pick that up and, so far, it's not prompting me, 'Are you still there? Do you still need help?' It's basically just a navigational tool, it seems."*

A marketing manager agreed that the purpose of the bots seemed to be exactly that – to navigate the prospective student through to the right place on the website rather than to synthesise information or provide engagement:

> *"I think that for large universities, where they get a lot of queries that are standard queries, then I think the chatbot provides help and support to quickly guide them through their website. It's good to provide navigation for the website. Some of it is good because it provides information, but mostly all the information was on the website. There wasn't any information that the chatbot was able to give me that wasn't on the website."*

The role of a navigator in this use case is also considered to be acting as an extended filter that narrows down the available information and presents to the user only what it deems relevant in a concise manner through a summary paragraph. This was the expectation of one UG student:

> *"The chatbots are really helpful to filter information. So, if I'm having problems with finding some different filters in the site, I could just ask the chatbot and it will probably give me the right directions. I usually use them for that. Just to get directions."*

Another attribute of functionality that would increase the usability of the bots is their availability any time of the day or night. As users operate in an ever-connected world where information flows constantly from organisations to prospective customers, the chatbots are that communication channel that never sleeps, rests or goes on holiday. All participants recognised this feature to be an advantage that the universities should utilise when communicating with students. One of the scenarios described by a PG participant was:

> *"I'm not necessarily going to be searching during working hours. And a chatbot can be there 24/7. If I can't sleep, then I won't have to wait to find out the answers. Whereas with a human, we can't expect them to be up at two o'clock in the morning waiting for you to phone. So, I'm guessing that having a chatbot there would be a very good thing for the university to be able to effectively talk to people all the time, as long as it's effective."*

A marketing manager recognised the importance of this attribute reflected on the current culture across customer segments:

"I think that the trend in marketing and technology is that people want the information right now. That's something that is regardless of age and gender. The trend is information. 'I want to have information available 24/7'. 'I want to get the answers to my questions now'. 'I don't want to wait 20 minutes'. 'I don't want to have a meeting'. 'I don't want to talk to someone over the phone'."

This discussion directly leads into the topic of the users' unwillingness to wait and their desire for speed in communicating with organisations. The consensus amongst the respondents was that speed of using the chatbot was a crucial factor in their intention and motivation to interact with it, although they were aware of its many other limitations. Attributed to users' increasingly "shorter attention span" and desire to find information in the "most efficient and quick way", bots are expected to act with immediacy 24 hours of the day. Here are some of the expectations described by marketers:

"I think you need to make sure that the answers that the chatbot gives are quick, if not instant."

and

"I think having a chatbot allows us to have that immediate interaction and engagement with the enquirer. It will allow us to engage with the student there and then in that moment. So, if they have a question that they want an answer on, then we can provide that to them. It's all about improving that user experience."

and

"One of the things that is emphasised a lot within my workplace is speed of contact when it comes to somebody that's enquiring. The bot will hit both

issues on the head: you're touching upon that speed of enquiry and making sure you're responding back, but you're also allowing that level of interaction to happen that is going to improve the customer experience."

Saving time for the students was the prime consideration when demanding speed in communication with the bots, which was not always the case. One PG student described their interactions as "a bit of a waste of time" and another said, "I want to know quite quickly if they can offer the course. Saves me having to go to a web page". In many of the interactions the participants were disappointed that the search through a bot had taken them longer than if they had searched the website themselves. One PG student summarised their expectation like this:

"My expectation is that AI needs to save time. My expectation is to see an answer, maybe just two links. Clearly, to direct me better. What I expect is that AI spends time to get to know me, so it can save time for me."

One approach to saving time is to predetermine the options for students to click on, rather than asking them to generate their own questions and options, which was seen as more time consuming and effortful. Students preferred the structured and efficient nature of predetermined questions, especially when these questions were relevant and well laid out. So much so, that the third bot the participants interacted with, which had those options as the only way to communicate, was preferred over the other two chatbots, which were either a free text chatbot or one that offered limited options at the start but switched to free text after that. One UG participant said:

"I found it more helpful and engaging than the other two. The other ones require you to type everything that you want. This is very guided and it can't

produce wrong answers that I'm not looking for because it's tailored, but I chose what I want to ask and it just guides me through it."

A similar view was shared amongst PG participants:

"I actually liked the X one with the options a little bit better in a way because you didn't have to work out how to phrase what you wanted to say to it."

and

"I wish you could just tick. Less typing and less chat, that gives you more information quicker. You could just select it quicker. 'I'm looking to do postgrad', 'I'm looking to do this', 'I'm looking to do that'."

The marketing professionals were also in favour of giving students pre-set options, especially when students might not know what questions they need to ask:

"What I like about this one already is that when you hover over the button, it provides you with some prompts of the sorts of questions that you might want to be asking when you make your enquiry. I quite like that, because sometimes when a student makes an enquiry, the student might not know already what they want to be asking."

Other participants, especially from the marketing professionals group, really valued the option to be able to type their own question and ask something specific for themselves:

"I prefer free text to feel like I'm having a conversation, but if they can't support that with relevant responses, then don't do it. I would then rather have something like the X University, which felt more like I was texting someone. I knew it was a bot, but at least it was responsive and appropriate."

and

> *“But I think this probably made it a bit worse in the sense that I wasn't able to type anything. It was simply me just interacting with the online chatbot in a way that I wasn't able to give my say in there.”*

and

> *“Normally this type of chatbot makes me tired, because instead of them letting me ask my questions, they keep asking me questions and questions and questions. And it makes me already tired of continuing with that. I am the one who wants to ask the question, but they take the time to ask me many, many questions.”*

When offered the option to have both free text and predetermined options, many of the participants thought it would be a good feature to have, especially for a user who had tried the options and was still not satisfied with the answers provided.

UG participant:

> *“I think it would be nice to have an option to be able to type as well, because sometimes if you have a really specific question, it might not be in one of these options.”*

And another UG participant:

> *“If you hover over this bot, it gives you some pre-set choices. If you like any of them, you can click on them but if you don't like any of them, you can click on ‘Chat with us’ to type. I think that's a really nice thing to do for a chatbot”*

One of the potential issues with free text spotted by the participants was the bot’s ability to support different languages or translate the conversation. Some of the bots had an option for the participants to chat in a different language and some of the multilingual interviewees attempted to use the option, however, none of them were successful. In principle, most of the participants were in favour of this option, appreciating this tool in view of the needs of international students and their parents who may not have English as their first language. Being able to receive crucial information about the programmes and the university in their own language was seen as inclusive and user friendly. There was a concern that this feature may attract students whose level of English was not at the right level for completing a degree, however, considering that chatbots form a very small part of the student journey and, quite often, just at the start of the information gathering stage, this was not a substantial concern amongst marketing professionals.

> *"Yes, I think that's a fantastic idea. Because we've got students from all over the world coming to universities for whom English may not be their first language, and their decision may require very nuanced information. If they can get that in their native language, then I'm all for it. I think that's a great idea, even though they will be studying in English at university, it still gives us a sense of, 'We actually understand that everyone's on their own journey and if you've coming from abroad, let's respect your culture and where you're from'."*

and

> *"Maybe not exactly for the students because they're asking questions for future in England, but it is better for the parents. If a future student is chatting alongside with their parents, and they don't know any English, I think it is*

better to understand each other and the parents knowing what they're saying, and if they're helping."

When the bots did not perform according to the users' expectations, as in the case of translation, or provided inaccurate information, many of the participants focused on the feeling of distrust such an experience may invoke and the negative impact this may have on their opinions of the bot itself as well as the university as a whole. These views emphasised the critical role that well-designed functionality plays in shaping perceptions of a university. Various aspects of such views are highlighted below:

PG participant:

"Potentially if the chatbot isn't good enough, the chatbot will be the thing that puts off the student. If you get to the point where you just can't get any information, maybe you're going to think less of the university. At the same point in time, I think most people can separate the technology from the institution. You know that the technology has evolution coming along."

And a marketing professional:

"Today I've seen three chatbots and I've been quite critical of them all. That does influence your opinion or your perception about the potential place that you want to study at and spend a lot of money on fees and accommodation. It's a big life change. What you offer and what services you have, whether it's an advisor on live chat or a chatbot, that's representing the university. It looks pretty terrible if that chatbot or advisor is not giving you what you want. It's not going to encourage you. It's going to put you off, more than anything, studying there."

The remaining three topics relating to functionality and usability were highlighted only by participants from the marketing professionals' group. When discussing the functionality that bots should have from a marketing perspective, several participants highlighted that the bot may be used quite effectively to segment the audiences that land on the university's website. This could be done through collecting personal information, the thoughtful formulation of the right questions, the collection of meta data about the users or the tone of voice used, including emoji's, GIFs and other engagement tools. This is how marketing managers described their potential use of a well-developed chatbot:

> *"I think they're missing a trick there again, where capturing that person's contact details, you could gain more information about who that person is, and at what stage are they at with their enquiry or whether they are already a student with us."*

and

> *"They probably say, 'Okay, our target audience that is using this bot is between the ages of 18 and 23, most likely looking for an undergraduate degree or are most likely looking for a postgraduate degree. And when they look for a postgraduate degree, they're probably more in their 25 to 30s'. So, whoever it is, might think, 'Okay, in connection with our culture, branding guidelines, tone of voice, this works'."*

When asked if they think UG or PG audiences are more likely to engage with the bots, the answers were not that clearcut. Some thought that UG students may be more inclined to interact due to their greater comfort with new technologies and prevailing tendency to avoid speaking on the phone:

> *"I think probably the younger audience, on a day-to-day basis, is more used to technology."*

and

> *"I think undergrads might engage more because I think that they're more averse to speaking on the phone. And even when they're chatting with their friends, I believe it's more likely to be over a device than it is using voice."*

There was, however, the general feeling that PGs are not far behind in their skills and willingness to engage with new technologies:

> *"It's always an interesting one when we make that distinction between undergraduate and postgraduate because some postgraduate students might still actually be very young. And I even think older postgraduate individuals, working professionals, we are all used to different ways of communicating these days and we're having to get on board with that both in our professional lives and our leisure lives as well."*

As well as the positive impact of segmentation of visitors to the website, marketing managers were asked to list other potential benefits of investing and launching a chatbot as part of their marketing communication strategies. The resulting comments could be grouped into benefits around cost savings, reduction of headcount and improved productivity of the programme consultants. Even though there is an initial outlay in preparing data, training a chatbot and fine-tuning the results, the long-term benefits seem to outweigh the initial financial investment. Cost reductions were seen in the possibility to streamline the staff structure:

> *"There may also be staffing cost reductions if you need less staff to answer questions. Then that would be a benefit to the university or even if it's just that those staff can be redistributed somewhere else within the organisation."*

and

> *"I think it's the expense, because what happens when you install expensive new technology, it may not be expensive, it depends on how well you develop it, but whoever's idea it is, ends up bearing the brunt of the investment at that moment in time, and it's generations down the line, it is people down the line who benefit from it, but haven't had to invest a penny in it."*

There were others who were not convinced that the bots will replace human agents in the recruitment process but may be able to provide them with a tool that will make them more efficient in their roles:

> *"The advantage would be when the Program Consultant gets in touch with the student personally, the bot has already answered 25% of the questions that were asked. And the human interaction would be focused on 75%. So that means we save time for some of the questions, we save cost of the hours. It'd be more of a quality interaction, because of the bot to a certain extent. Better productivity for the Program Consultants."*

To summarise the views of how effective chatbots can be if deployed as part of the student journey, the marketing managers were finally asked to identify the key performance indicators they would use to evaluate the bots' performance, desired impact and return on investment. As with human agents, performance metrics can be divided into two categories: quantitative and qualitative. Also, they can be evaluated against short-term gains or long-term benefits. One marketeer gave some examples of both types of metrics:

> *“Well, there are two types of metrics that are important to this. There's the hard metrics – how long do people stay on this, how many questions do they ask, did they go to a landing page, and they'll need to look at the landing page metrics as well. But also, I think you'd need to go out and do some qualitative work afterwards and say, ‘Okay, so how did it make you feel? What was the vibe like?’, so you can put the hard and soft metrics against each other and then make sense of it. Because the hard stuff will tell you what happened when, but it won't tell you why."*

Many other examples of metrics were also proposed that would help evaluate the effectiveness of the bots: “if someone’s had to rephrase”; “how the conversation ended”; “is the person on the pipeline to application”; “increased dwell time on the website”; and, ultimately, “what is the correlation between people who have used the bot and have become students”.

In the next theme we explore the issues of trust and privacy that may trump users’ appreciation for functionality and usability.

4.3.3 Theme 3 – Trust and Privacy

The third theme of Trust and Privacy is defined as the participants’ perceptions of CA’s’ benevolence, integrity and competence that facilitate a successful interaction with a CA. The associated codes and keywords identified in the analysis have been summarised in Table 4.5 below.

THEME	DEFINITION	CODES	KEYWORDS
Trust and Privacy	The characteristics of benevolence, integrity and competence that facilitate a successful interaction with a conversational agent	privacy concerns	• Not worried • Prefer not to share • Unless required • Don't mind • Don't think about it • Hesitant • Asking for details early • Only when asked personal questions • More trustworthy
		personal information	• Depends • Name is ok • Email not ok • Don't mind sharing • Spam • Data leak • GDPR • Capture at the end • After meaningful conversation • After qualifying questions
		bots collecting data	• Collect my data • Data capture • Accumulate data • Response times • Level of engagement
		check the answers	• Check the information • Blindly believe • Double check • Wrong information • Get info verified • Confirmation • Not up to date • Cross check • Things change

		ideas	• Options haven't considered • Useful • Give ideas • Plant a seed • Ideas you have not thought of • Got me thinking • Scenarios • Didn’t think about • Prompt
		recommendations	• Check out • Helpful • Not trust blindly • Consider • Interested to know • Useful • Trust to some extent • Suggest • Narrow choices • Not getting personal opinion • On par with human • Based on same information • Trust the bot more • Doesn't make mistakes
		human-lived experiences	• Somebody that studied • Someone that taught the course • Trust less than human • Human Interaction • Human experience • Human advise
		confusion	• Don't understand • Confused • Frustrated • Personal details • Confused with live chat • Distract • Not obvious • Transparent

		third-party bot	• Not aligned • Bolt-on • Not specialised • Not of the system • Doesn't belong • Not relevant
		purpose	• Purpose of bot • Keeping up • Student journey • Replace humans • Classify users • Modify answer • Clear goals • Progress in funnel • Different path

Table 4.5 Theme 3 – Trust and Privacy (Source: Author, 2024)

The themes of trust, privacy, and ethical application of AI and conversational AI tools often feature in the academic literature and commercial publications. There is no unified definition of the concept of trust in the literature, however, when present, it allows individuals to "overcome perceptions of uncertainty and risk and engage in trust-related behaviour" (Brill, Munoz and Miller, 2022, p.54). Trust is described as a three-dimensional concept comprising: (1) the trustee will not act opportunistically (benevolence), (2) the trustee will be honest and keep their promise (integrity) and (3) the trustee is able to perform as expected (competence). When that trustee happens to be a piece of technology and not another human being, the concept of trust becomes even more complex as it considers not only human factors, such as motivation, knowledge and personality traits, but also AI factors, such as transparency, explainability and ethical design (Knickrehm, Voss and Barton, 2023).

The concepts of trust and privacy are quite distinct in their definitions and yet very interconnected and interdependent in the minds of consumers. A change in one would most likely lead to change in the other. For example, an incident leading to an erosion of trust would heighten privacy concerns that may have laid dormant until then. This is because privacy can be conceptualised as a “social contract” between the CA and the user, where the individual consents to certain limitations to their freedom and to share personal information in exchange for security and personalisation of services (Schmager at al., 2024). CAs and users enter into a social contract when they engage with each other, and personal information is provided with the expectation that it will be used responsibly and safeguarded against misuse. Violations of such contracts result in an erosion of trust and reduce a user’s intention to continue interacting with the CA (Bélanger, Crossler and Correia, 2021).

In the context of this research, the participants were asked a series of questions about their attitudes and opinions relating to trusting the bots in a number of scenarios. Firstly, they were asked to articulate if they had any privacy concerns about the way the bots interacted with them or used their data. When this question was asked to the UG participants, many of them admitted that they had not even thought about this and had not considered this to be a problem; hence, they had no privacy concerns at all. One UG participant was very straightforward:

> *“Probably I should be worried, but I am not really.”*

Another admitted to their lack of knowledge on the topic:

> *“No, it doesn't really concern me. I don't particularly know that much about data and things like that.”*

And another relied on the security of the website:

> *“If I'm in a protected site, which is protected by some kinds of cookies, I'm not stressed about data leakage or taking things from a laptop. So, no, I don't think about it.”*

The representatives of the PG group were more aware of privacy issues that may arise from bots collecting personal data; however, this group also did not display strong feelings of concern. Their slight hesitation was expressed as this:

> *“I don't think that comes to mind. I think it starts coming to mind when the bot starts asking me more personal questions or when the bot needs more personal details from me. I think that's when I start thinking about, ‘Oh, why do they need these details? What's this going to be used for?’ But I think if it's more generic, I'm quite confident and I feel comfortable using the bot.”*

One participant went as far as to imply that they would trust the bot more than a human being:

> *“No, I have no concerns, because I think they are even more trustworthy than real people for data storage and collection and privacy.”*

Most of the marketeers immediately picked up on the issue of General Data Protection Regulation (GDPR) compliance and how the bot was designed to demonstrate the institution’s commitment to protecting personal data. This is how one marketing professional explained the approach:

> *“There should be serious consideration given to data management and how we are capturing the details of people who are making those enquiries and making sure that the data itself is secure, it is stored in a safe manner, legally compliant as well. So, making sure that we follow GDPR guidelines when it comes to building these chatbots, considering privacy regulation, making sure that the data itself isn't shared with anybody else, that we're actually receiving consent.”*

The discussions on privacy inevitably led to participants commenting on the bots' approaches to collecting their personal data. One of the bots asked for the name, email and country at the start, before the conversation was allowed to commence, the second bot did not ask for personal information at any point in the conversation, and the third bot asked for the first name only to personalise the information and after providing some of the information asked if the user was willing to provide their contact details to be sent further information including a question asking their permission to be contacted. The UG and PG participants predominantly liked the approach of the third bot, while the marketing professionals liked the certainty of being able to collect user data at the start but understood why students may not like this approach. This discussion inevitably led back to the concept of purpose for the deployment of chatbots.

Here are some of the comments of UG and PG students during their chatbot interactions:

> *"It should be at the end. After the chatbot builds a proper meaningful conversation, then it makes you feel that it qualifies my questions, then it should be at the end. But maybe the first name only can be in the beginning to give you a personalised human side of greeting, but asking for an email address should be the last one."*

and

> *"You immediately think you're putting me on a list and you're gonna spam me with loads and loads of stuff. And I might not even want to come and study with you, which is a bit annoying. I think it's nice to have as an option, if you*

want to give your details, rather than that being more of an obstacle in the chat that you have to fill out and get through."

The marketers sympathised with the students' perspective:

"We certainly find in my organisation that students hate having to give their data at the point of just an enquiry or fact finding. They're very switched on to marketing. They know why they're providing that information. And they know that it's not necessarily in their best interest. They want to go and find the information within their own timescales, not have it broadcast to them at times when they're not looking for it. For just a general enquiry, which is what this is, I think, not needing to provide data is a good thing for the student."

Marketers also expressed positive comments on a feature where the personal data is collected as part of the conversation and not in the shape of an enquiry form:

"Gathering information this way rather than on an enquiry form is a good way because you've already had some engagement with the student, and you've provided them with some information already. And they're still interested."

Perhaps a slight concern amongst students was the bot's ability to collect additional data on them that they had not intended to share, such as meta data, location, website search history. This concern, however, was not shared by marketers and was in fact seen as an expectation for the bot to provide as part of their functionality. This dual perspective on the topic is evident in the comments provided. A student commented:

"If it's some kind of chatbot that collects data from your laptop, location and stuff like that, I think that's a big disadvantage. Maybe, if it's a bad chatbot, it could download some important data from your laptop."

This view of disadvantage was actually seen as an opportunity by marketers:

> *“I think also from our perspective, we could probably accumulate quite a bit of information about the student, about their level of engagement, the kind of response times and things from just observing how they engage with the questions etc.”*

On the one hand, the bots were collecting personal data, and on the other, they were providing information to the users linked to the questions being asked. The accuracy of that information, as we have seen from earlier discussions, was questioned and that led to the concept of trust in the bot and its ability to provide trustworthy answers. Many of the participants spontaneously revealed that they would not implicitly trust the answers provided, even if they came from a university chatbot, but will perform checks on the data to ensure that the answers were correct. When asked if people can trust chatbots to get reliable information, one UG student articulated:

> *“It is not that people would rely on chatbots, but that they blindly believe the chatbots. They do not double check the information that they produce, and sometimes they produce very wrong information. Taking something for granted from a chatbot is like the worst thing that you can do.”*

A PG student described the thoughts that might be going through their head when evaluating chatbot answers:

> *“I might think, ‘Well, I think I need to get that verified’. I wouldn't take that as absolute confirmation that that would be the case. It would be, ‘I need to take that further and look at it in more detail’. I wouldn't think it's weird if they were going to send me the prospectus for the course.”*

Answer accuracy was also at the forefront of the marketers' mind; it was widely understood that if the bot did not perform well in that respect, then that would create a problem for the university and eventually threaten the institution's credibility:

> *"The reason why I prefer the first one is just because of the answer accuracy. If the bot doesn't answer correctly, I think I would want to double check. I will not trust it anymore. With bot number two, I just don't know how the university would be able to contact them because the answers were incorrect, and they also don't have my information."*

The participants were quite happy to trust the bots' ability to generate and offer ideas that the student may have not previously considered. LLMs that power generative AI tools such as ChatGPT are now well known for their ability to assist in brainstorming and idea generation. Even though none of the university chatbots used for the interviews had those generative AI capabilities, they were still able to provide interesting and valuable alternatives that the students had not considered previously. This was mainly due to the well-considered design of options and keyword matching. This is how some students expressed their delight in being offered additional information that formed ideas:

> *"When I was presented with options, there were some options which I hadn't considered and actually new questions came across my mind – what useful questions can I ask and what else can I find out about my future studies."*

and

> *"And sometimes they send me links to something that I probably have thought about, which I probably wouldn't have looked at, at that point, but probably would have looked at, at a later stage. So, they will prompt me to look at other*

things about a particular area or topic or something I was looking at. So, I think it's quite useful having that chatbot, because it will maybe throw up some scenarios that you might not have even thought about."

One participant even said that perhaps chatbots are even better than humans at generating ideas:

"That would be only an idea for me. To use it as an idea. I think machines can give us more precise, closer to what you want, ideas than human being."

When pushed to consider not just generating an idea through the use of a chatbot, but getting a recommendation from a chatbot about what to study, participants became more cautious. They were asked to consider not only how much they would trust that recommendation, but also if they would trust it more or less than a recommendation that came from a human being. Trust in a recommendation from either a bot or a human did not score very high on the trust scale. Almost every participant asserted that they would look at it, consider it and look for information through another channel to confirm the validity of that recommendation. One student was particularly interested in what the bot had to say:

"If I say, 'I have these interests. What could I learn? What should I learn at university?' and it referenced some programmes and gave me an answer and explanation why it's referenced them, like 'You have these interests, so it's good to go here' or 'You have these interests, it's good to learn this'. It will be helpful to people, yeah."

Another student compared the bot to a career advisor:

"If you're not extremely sure, and the chatbot gives you a career test and it gives you several choices. For a person that doesn't know what they want in the

future, it could be helpful. It's a computer, so it does know a thing or two about the programmes. Maybe it could be useful for some people."

When asked to compare the trust level between human and machine, there was a wide diversity of views. Some would trust the bot more, some less and some the same:

"I'll definitely trust the human's opinion over the bot, because I feel like with the robot, especially if you don't know where you want to study, there's more multiple factors that will affect how you want to study so if the bot can't remember the conversation and remember information from before, then it definitely cannot have a better opinion than the human."

and the opposing view,

"I would trust the bot a bit more than the human. It's a machine, it doesn't make mistakes. If it's programmed correctly, it wouldn't make mistakes. Human beings do make mistakes because they're human beings."

and a balancing argument,

"Probably the same because if it came up with a recommendation, I'd still go and do all the reading. I'm not going to just suddenly sign up without going and reading it and researching it and checking it out and maybe checking the university out more. It's the start point, it's just the push in the right direction to where I'm going and look for the information."

One marketer suggested that to make bots seem more reliable in their recommendations, there is the option to gamify the process:

"If you are 17, you'd probably prefer to do something with the bot if it made it more fun and said, 'We're going to do a quiz'. Based on their responses and

they ask you about what A levels you studied, what projected A level grades you are going to get, what careers that they're thinking of from graduation, potential salaries that they want upon graduation."

For the people that were not ready to trust the bot's recommendations, one notable objection was the lack of a human-lived experience to inform the recommendations. This was summarised in the view of this student:

"I think I would trust the chatbot response less than a human response, because a human response will be coming from somebody who's actually studied the course or taught the course, whereas a chatbot would just be programmed to pick out keywords that I've used. So, I would look into the options that they suggested, but I would trust them less."

And another student confirmed:

"I think at this stage of the results generated by AI, considering that I wouldn't trust compared to human, because people give suggestions based on their own experience. But AIs, they don't have a human experience. And yes, it's useful, but I wouldn't trust it more than a human's advice."

Another aspect of trust that emerged in the conversations was around the users' confusion as to whom they were speaking with. In some instances, the users admitted not being certain if they were speaking with a chatbot or they were participating in a form of a live chat where the respondent is a human being. That uncertainty led to a feeling of mistrust in the whole process of interacting through this type of interface. Participants commented:

"I think some people don't really understand them. Maybe, people from some countries who haven't got as much experience with AI, they might be a bit

confused by the chatbot and think that they're speaking to a real person. So, it could become quite frustrating for them."

and

"Back in the day it was live conversation in the chat bubbles of websites. These chatbots I think distract the visitor from exploring the website."

To avoid confusion of this type a marketing professional suggested:

"I'd also say, right from the start, it should have introduced the fact that it was a bot. Whilst for most of us, that would be obvious, there would be some students who may not appreciate that this was the case. I would say that, on the one hand, it is being transparent, which, I think, is the most important thing. On the other, it may be off putting."

A privacy concern that was highlighted by some participants was the indication that the chatbot technology was provided by a third party and not developed by the university themselves. This brought forward concerns not only about how the data would be used, but also about the accuracy and relevancy of the answers provided. Chatbots being provided by a third party was seen as being disconnected from the university's communication strategy, and it emphasised the perception that it was just an added feature rather than an organic component of their communication channels. This was seen in general as a negative feature that caused concern. Their views were expressed like this:

PG participant:

"The bot is not really the bot of the system. The way it communicates, it feels like a third party. Even though it can be developed by a third party, it's not

aligned with the requirements of the university and its potential visitors. It's like, I am visiting the website, and there is another person coming and searching with me on the website, and then he's directing me and giving me answers."

And a Marketing Professional:

"If you look at the middle one, that was supplied by a company called Futr.ai, so it doesn't feel like it's the university. It feels like it's a 'bolt on' that's come in."

A large proportion of mistrust can be attributed to the lack of clarity about why the chatbot was deployed in the first place, what is its purpose and what is the university trying to achieve by offering this method of communication. If users decide to use the system having one set of preconceptions as to how this tool might be useful to them, but the marketing team has structured the conversation flow in a different way to achieve a different goal, then the discrepancy between these two aims and objectives would be likely to lead to a loss of trust. Users usually engage in conversations with bots for the purpose of navigating to the right part of the website to find the most relevant information they are looking for or to generate ideas about their choices if they are at the very early stages of their search. Marketing professionals are interested in reducing the workload of programme advisors by fending off frequently asked questions and to collect data about the people coming to their website who may one day become their students. Here is how a PG student described their conversational journey:

"If I have a really clear goal of what I want to know from a bot, then I'm probably there."

Another student recognised the value of being classified in a particular user group so that more targeted answers can be displayed:

“Perhaps if the bot asked you, ‘Are you a student?’, ‘Are you a parent?’ or ‘Are you a career advisor?’ to classify you, after asking your first name, I think then the second question can be, ‘What are your circumstances?’, ‘What's your situation?’ Even, it can ask for the age range, so it can specialise the answer.”

Marketeers also appreciated that a bot should not have too many goals to fulfil if it is going to be effective at any of them. One marketing professional put it like this:

“I think they need to figure out two things. Who is going to use the chatbot? What's the purpose? If the intention is a new student, then that journey is totally different. What you want to do is make it easy for that student to navigate, but you also want their contact details because you want to close them. So, if your goal is to cater to new students, then the experience is different. If your goal is to stop unnecessary enquiries coming in, like to get rid of the white noise, then you would put in the X university type. It helps the white noise be deflected quite quickly.”

Marketers also acknowledged that currently some universities may have chosen to develop and deploy a chatbot simply for the goal of keeping up with the competition and so that they do not fall behind the technological trend and customer expectations. Marketers were cognisant of the changing technological environment that revolutionises how students expect to communicate with universities:

“I think they will be ubiquitous because they are seen in all consumer experiences at the moment. So, I think, any institution that didn't allow that would be seen as a little antiquated in time, as not being as current. So, even though it may not necessarily make the student journey any easier, I think

institutions, including universities, have to be on the same playing field as their competitors."

Users' sense of trust and confidence in chatbots is dependent on the emotions they experience during the conversation experience. These factors are explored in more detail in the next theme.

4.3.4 Theme 4 – Emotional and Perceptual Aspects

The fourth theme of Emotional and Perceptual Aspects is defined as the emotional and perceptual aspects that influence a user's willingness to engage and continue engaging with CAs. The associated codes and keywords identified in the analysis have been summarised in Table 4.6 below.

THEME 4	DEFINITION	CODES	KEYWORDS
Emotional and Perceptual Aspects	The emotional and perceptual aspects that influence a user's willingness to engage and continue engaging with conversational agents	normal	• Strange at first • Used to it now • Normal experience • Use quite a lot • Not different • Self-explanatory • Basic • Limited
		annoyance	• Annoying • Expectations • Not helpful • Not frustrated • Knew will not get information • Started with low expectations

		frustration	• Frustrated • Not able to answer • Normal to give wrong information • Disappointed • Take with pinch of salt • Going round the houses • Don't understand • Overload • Putting me in a loop
		expectations	• Learning • Expected to fail • Expectation low • Impostor • Pretending • Serve as baseline
		giving up	• Look by myself • Give up • Couple of chances • Not useful • Not giving answers • Find the info myself • Gives only general answers • No straight answers • Useless conversation • Doesn't remember • Got bored • Drive insane
		uncomfortable	• Up to me • Fake info • Marketing emails • Comfortable • Normal to ask questions • Talk to human • Anonymity

		surprise	• Expect • Funny • Did not provide detailed info • Expect direct answer • GIFs • Not formal • Relaxed • Nice • More casual • Pleasantly surprised • Clear • Didn’t work
		ease of use	• Easier • Bot understands • Harder for the bot • Pleasant • Better • More informative • Gaining more knowledge • More open to using • Buttons • User friendly • Just click • Hard to navigate • Have proper skills
		layout design	• Prefer side-to-side scrolling • Compare • Takes ages • Space on screen • Quick to see • Colour • Text font • Broken down • Short • A lot of information
		welcome message	• Nice gesture • Brief introduction • Quick answer • Depressing • Enough information • Short • Informative

		personality	• Personable • Person • Bot name • Feels better • Creepy • Help remember • Human element
		future use	• More • Less • Give it a chance • Improving • More readily available • Becomes the only way • Fully functional • Application process

Table 4.6 Theme 4 – Emotional and Perceptual Aspects (Source: Author, 2024)

The theme of emotional and perceptual aspects sits firmly in the field of human–robot interaction (HRI), which has gathered significant attention in recent years with researchers and scholars seeking to understand the psychological aspects underpinning the interaction between humans and AI tools (Zhao, 2023). The theme became so important that a brand-new paradigm named "Computers As Social Actors" emerged in the literature as early as the 1990s; this paradigm asserted that people either tend to respond to computers according to principles similar to human–human interaction or perceive them as having less agency and emotional capability than humans (Nass, Steuer and Stauber, 1994). Academic disciplines attribute various components to what constitutes emotions: evaluative, physiological, phenomenological, expressive, behavioural and mental (Stark and Hoey, 2021). The theme proposed here is limited to the emotional and perceptual aspects influencing communication, which are explored exclusively from the perspective of the humans. What this theme does not seek to uncover are the technological attributes needed to imbue chatbots with abilities to recognise human emotions or display the perception of emotions.

After interacting with the university chatbots, the participants were asked to reflect on the emotions they experienced during the time they were conversing with the bots. Without any prompting from the interviewer, many were unaware of having any strong emotions, either positive or negative, during the experience. In fact, many of the UG participants labelled the experience “normal”. Here are some of the recounts recorded:

> *“I found it quite a normal experience, because I use this type of AI for quite a lot of things. Like with my college work, I use AI quite a lot. So, it's a bit strange at first that they've given me these automated answers, but I think I'm quite used to it now.”*

and

> *“It was normal. These bots that are integrated here are very basic. They have a limited set of functionalities. They're very limited.”*

and

> *“I just find it quite normal. Most of the chatbots are doing it. They ask for the name at the beginning. They normally say your name in the first line of the chat. Well, to be honest, I didn't even notice that. It has become quite normal now.”*

The feeling of being a normal day-to-day experience may have been due to the fact that these participants have already chatted with bots before or because the perception of simple functionality did not cause any anxiety even if they were not accustomed to this particular technology. One student equated the experience to searching for information on the website:

> *“Let's say it was all quite relevant, just not hugely different from just using a website. If I hover over courses, and it says undergraduate courses, it's quite self-explanatory.”*

When prompted with the question if they felt any annoyance or irritation during the experience, the answers were quite similar across the board:

UG participant:

> *“I wouldn't say it was annoying or something like that. It's just I don't have high expectations for the chatbot, so I don't expect much from them. If they give me even a little bit of information, it's still helpful.”*

And a Marketing professional:

> *“Not as annoying as the old bots used to be. Anything that was not what the bot wanted to hear, the enquirer would just receive, Oh, our working hours are blah blah blah’."*

However, the feeling of annoyance sometimes escalated to a full feeling of frustration. The instances when that happened were predominantly when the bot did not meet the user’s expectation or did not function as anticipated. Here are some examples from PG participants and Marketing professionals that were recalled after the experience:

> *“If you've got an answer that you want and it takes them so long to actually, first of all, splurge out an answer and, second of all, the answer may not be what you're looking for, I think generally, the experience is relatively frustrating. I just feel the experience is generally frustrating.”*

and

"It doesn't feel like you're engaging with somebody that is really understanding your question. Already the response, 'Here is the closest match we have found to your question', this will probably frustrate me."

and

"Yeah, definitely frustrated, especially when they're putting me in the loop, giving me the same question, or when they start asking so many questions."

One PG student's frustration was so intense that they refused to continue interacting with the chatbot:

"This one would drive me insane, I think, because you just go round in a circle. It would make me really irritated and I would probably just give up."

Other incidents that caused frustration were when the bot did not provide a relevant answer to a simple question, provided wrong information about open days, gave general answers to specific questions, didn't help narrow down the search, provided very long answers and overloaded with information.

Many of the participants reflected that their frustration may have been caused by a mismatch in expectations. When participants had one expectation, but the performance of the bot did not match that, they would either try again and repeat the exercise and attempt to get better results next time round or completely give up on using the bot. This sentiment was expressed with these statements:

PG participant:

"I would say there were parts where I found it frustrating because I think I must have typed in the same question three times. I think because I have this

assumption when I'm using technology, I think if I type something in it will just work."

And an UG participant:

"I just knew that most probably I wouldn't get the information that I needed directly from the chatbot, but it would help me a great deal to get a little bit more familiar with the programmes and the courses that the university is providing. I was hoping that it would provide me with some direct answers, but during the process I realised that most probably I won't get those answers."

Sometimes, the bots did attempt to set the expectations by pointing out they are still learning and improving, but sometimes that backfired as the users then developed the attitude that the conversation experience would not be satisfactory. A PG student commented on one of the bots that had a female name:

"At the beginning, she said that she's learning. And I think it almost sets her up for she's not going to be able to perform. And she wasn't able to. I was almost expecting her to fail. I know that it's good to say to people, 'I'm in development, I will get better', but at the same time it sets the expectation bar so crushingly low."

Managing users' expectations is often done with the intention to be transparent about the current capabilities of the chatbot, the learning status and potential limitations as that is seen as an attempt to establish trust and balance positive user perception for a better overall user experience. When those expectations are not managed well, what happens more often than not is that users give up trying to have a conversation with the bot and revert to other methods of gathering information, such as through the website, Google Search or contacting the institution via email or phone. When asked at different points during the interview if they want to give up or continue attempting to get information, many participants were willing to give the bots up to two attempts before moving on. Here are their comments during the chat experience:

UG participant:

> *“I would say after two times you can see that it's not going to work again. Maximum two wrong goes, and then I'll go and look some other way. I think after one or two questions, you can kind of tell if the chatbot’s going to work properly or not.”*

And a PG participant:

> *“Probably I would have given up after the second question, especially with the other one where it then went back to the start, where it hadn't actually remembered and then sent me back to a more of a generic answer.”*

And a Marketing professional:

> *“Because I've tried twice, I've rephrased the question, and I want to see exactly a master's degree and the bot is only giving me entry requirements for undergraduate courses, I personally would go to the website. And I'll start looking for the website information.”*

Participants were also prompted with a question about any feelings of discomfort during the chatbot experience. This feeling was not present in many of the participants and when they admitted to feeling discomfort it was usually mild and associated with the activity of sharing excessive personal information at the start or early in the conversation. It would appear that any feelings of discomfort are rooted in considerations around privacy, potential misuse of personal data and expectations as to how the data will be used. UG participants, in particular, were comfortable with the chatbot experience:

> *“I think a lot of sites ask you to give personal data. So, I was quite comfortable with it.”*

and

> *“Definitely not uncomfortable. It's just that these questions, I get them everywhere in almost every site. So, it's up to me to decide whether I should give the information or not. So, they're not making me do it.”*

and

> *“Felt uncomfortable only when Tom [human] pinged up. But before that, because it's all completely anonymous and I think I probably prefer that anonymity to it rather than providing all of my details, knowing that they're just going to start bombarding me with spam after that. The anonymity makes you feel better.”*

The participants were then prompted with a question about whether they found anything surprising in their interaction with the bots. The surprises came in two varieties – both good and bad. The positive surprises were associated with the warm and friendly tone of voice of one of the bots and the use of GIFs, emojis and YouTube videos, which are not common features in chatbots. The unexpected incorporation of multimedia elements introduced an element of novelty and entertainment, which challenged conventional expectations of what chatbot conversations should look and feel like. Here are some of the comments recorded during the interaction:

Two UG participants:

> *"I didn't expect the GIFs here on the third one. They are funny."*

and

> *"I mean, the GIFs in the one bot, they were funny. I think it makes the university seem more friendly. Yeah, more welcoming."*

And two Marketing professionals:

> *"Oh yeah, the cat. That's unusual. It's fine, but who came up with that idea? That was kind of random. And then there's another one there as well, which I missed. I suppose they're trying to appeal to a particular audience."*

and

> *"I think it is surprising for me to see GIFs in a bot because it makes me feel much more like it's WhatsApp or something like that. It has more of a feel of a social app interaction rather than a chatbot, which is actually what it is. It's a more modern, digital conversational piece rather than a technology experience of a chatbot that's just barely functioning. It is actually more conversational, even though they're not allowing me to put in the question."*

Another good surprise was when the chatbot worked as expected. Some participants admitted to being pleasantly surprised when they actually received a relevant and well-structured answer from the bot:

A Marketing professional:

> *"I was surprised by the X university one where they had so many options, I thought it was really well thought out. I was surprised in a good way not in a bad way."*

And an UG participant:

> *"I was pleasantly surprised with this one, because I've never used a chatbot where it's been this clear before. So, I'm surprised with that."*

One PG participant was even surprised that the universities had chatbots in the first place:

> *"Firstly, I was surprised that universities have this, because when I originally did my bachelor's I remember the process was very lengthy having to find a lot of information. I think the process is a lot more efficient. When I applied for my bachelor's degree, I think it took me a lot longer, probably half a day, just to find out all the information I needed, as opposed to now in the chatbot where I'm able to find out everything I need from just a click away. I'm quite surprised how advanced the system is in that aspect."*

However, there were also negative surprises, especially when the chatbot did not meet the user's expectations:

UG participant:

> *"I was a little bit surprised that the chatbot did not provide some more detailed information about some topics, but just links. Maybe, this was a little bit surprising for me just because when I'm asking a direct question, I'm expecting a direct answer."*

And two PG participants:

“I’m not surprised that the chatbots weren't that helpful. I am a little surprised that X university just went round in circles giving me the same kind of information over and over.”

and

“Definitely the bad surprise was for the one that told me to come back during working hours. Definitely, this is something that you don't expect to see. Clearly when you're using an online chatbot you want to have it 24/7. That was quite a disappointment.”

Pivoting away from emotions and focusing on the perceptions of the users, the topic of how easy they found the experience of chatting with bots revealed an interesting range of opinions and attitudes relating to a variety of functionalities and usability features. Some users appreciated the simplicity and efficiency of the bots offering pre-set options, while others admitted that they may have to learn a “special language” that will help them communicate better with the bots when writing their questions or prompts. A selection of UG students shared their thoughts:

“I think it's very easy, especially the last one with the buttons. I think it makes it a lot easier for someone to find their way around the website.”

and

“The third one didn't allow me to type my own question, but I think it's even easier, because then it's sure it will understand correctly. It's not harder for me, but I think it's harder for the chatbot to really get what you're asking for.”

The PG students echoed the opinion that the chatbots were not difficult to navigate:

> *"It's quite straightforward. There are differences there, but you're not going to get one that's exactly the same or doesn't seem to be that way. No, it's not difficult or challenging."*

and

> *"I would say it's quite easy in the sense that I've got a positive experience. So, depending on the bot, I think I am quite comfortable in using it. And I think it also depends on the overall experience that I get from it, which factors in my overall experience. So, I think, all in all, I do find the bot to be quite efficient when it's working."*

and

> *"This one was incredibly user friendly, and I think anyone could just click on the options. That's fine. I think the ones with free typing, they are certainly getting more common and they're available on more websites than previously."*

Part of the consideration of how easy a chatbot is for the user is linked to the layout and design of the chatbot interface. Chatbot icons tend to be positioned at the bottom right-hand corner of a web page and open a vertical narrow window when the chat is initiated. Participants expressed a variety of preferences and critiques of the designs they experienced; they favoured a clear and engaging design, user-friendly navigation and considerations of the desired functionality to balance aesthetics. While one participant "preferred the side-to-side scrolling" as it was easier to track the option and make comparisons compared to a drop-down option, another "hated the side-to-side scrolling" calling it a recipe for disaster because in their opinion users should be continuously scrolling down for smoother user experience. Some of the PG participants noticed the visual attributes that made the experience better:

> *"I personally prefer the X university bot, just because I felt that it was quite quick to see, the colour and the text and the way it's formatted was quite short, and it was quite easily broken down for me to process the information."*

and

> *"I think it's going to all come down to how good the designer is. The X university designer has obviously thought it through really well. I like the ones where the chat comes with you. I wouldn't have got that the cross button just minimises it instead of making it go away."*

and

> *"What is the advantage of a chatbot if it's just summarising and not making everything easier for us? But it is just giving me a lot of information to read in this small window."*

A design feature that was noticed and commented extensively on was whether the chatbot followed the user and retained the conversation as it opened further tabs with information. On some occasions the bot started the conversation from the beginning as if this was a brand-new user, and on other occasions it followed through with the user and allowed for the conversation to continue in the new tab that displayed all that had been discussed up to that point. Two Marketing professionals observed:

> *“Even though it's opened up a separate web page, the chatbot messaging still continues. So, I've not lost that chat or have to go back to the previous web page, which is quite nice.”*

and

> *“I go to more information, it's not there. The fact that there is no icon for me to go back to afterwards is an issue, unless I click on where the bot is active. When the bot is active, and when I click on it, my history is there, which is good.”*

Part of the design choices made with each of the bots was the presence and content of a welcome message. One of the bots did not have any message or instructions on how to begin the conversation, another had a lengthy message giving a lot of information about the opening hours and the enquiry form, and the third one had a short and personal message welcoming the users. Here are the participants’ reactions to these three types of welcome messages:

Two UG participants said:

> *“I liked the welcome message. It was short, informative, good. When I wrote my name in, it welcomed me. It was good. I liked it.”*

and

> *“I think a brief introduction is probably best, because if people are using a chatbot, they're usually looking for quite a quick answer to that question. So, I think if people have a lot to read, then that can be quite inconvenient. But if people don't get any greeting, then it feels really obvious that you're not speaking to a person and some people don't enjoy that.”*

And a PG participant:

> *“I really insist on them greeting me of course. Let's say I am stepping into a university, I would expect somebody to be at the reception, somebody greeting me, saying ‘Hi’. Otherwise, you're just stepping into an empty building.”*

The marketing managers were quite surprised by the chatbot that chose not to welcome the user and pointed out potential issues with that approach:

> *“We don't get anything? Okay, right here, this is an issue. From a marketing perspective, if someone opens the chat, you should receive a ‘Hello. Hi, I am Valeria, your assistant today. How may I help you?’ So, they are literally losing customers because if I were not in the ‘marketing mind’, I'd be like, ‘Wait a second. What? Nothing?’.”*

and

> *“There wasn't an opening message from the chatbot to initiate the conversation. It was just a blank screen, and I wasn't sure if I was expecting to receive a message to start off the conversation from their side. I think it would be nice for them to perhaps start off with a prompt for the enquirer, even something as simple as, ‘Hi there, how can I assist you with your enquiry?’ or ‘How can I help you today’.*

The personality that a chatbot may adopt holds a special place in the perceptions of users; a chatbot’s personality could make students feel at ease and make the interaction more personable and friendly. This personality is often expressed via the adoption of a name that gives the chatbot anthropomorphic features, such as having an avatar or a voice to communicate via speech. Participants had varying views on this approach:

UG participant:

> *"Well, with names, it depends on the person but I'm seeing it as a fun little detail to give it personality and to mimic conversation with a real person."*

And a PG participant:

> *"It's good that they have a name, but instead of trying to replicate a real person's name with a similar name to the university, it would be better to give it a 'bot name', like technologic one word or keyword, and I would know that it's an AI bot."*

And a Marketing professional:

> *"I think the way of making it a bit more personable. Yes, we know it's a robot, but having a bit of personality to it and the GIFs and so forth. Even if they weren't my cup of tea, I understand that for their target audiences it is important."*

The difficulty of choosing the right name and avoiding some of the pitfalls described in the literature were summarised by this marketing manager:

> *"I read that the reason why all these tech companies give artificial intelligence names, whether it's a chat or tech apps such as Alexa and Siri, they want android names, because it makes it more relatable. Now, the question here is a question of gender. So, why does it have to be a woman all the time? Is it because women are more likely to be more related to customer services and*

selling? In the past, it has been very gender driven, that women are more of a nurturer character or a mother-like character that people go to for help."

The attribute of personality was also linked to the use of GIFs and emojis. One marketing manager shared their thoughts on the "human elements" they spotted in the design:

"It seems as if they've tried to incorporate a fun, happy chatbot experience. Which is good, because they know that this chatbot is a non-human element. So, to bring the human element in, they've used people and names. They've brought the emotion out during the chatbot process, which is good. If you see, 'Nice to meet you', this is personal."

The final perceptual attribute teased out of the participants was when they were asked to imagine the future and estimate whether they would use chatbots more, less or the same as at the present moment and how chatbots might be used specifically in the student recruitment process. Some interesting perspectives on both ends of the spectrum emerged. Some were enthusiastically optimistic about the future, whereas others displayed cautious scepticism about the capabilities of the technology. A majority of the UG students hypothesised that they would use chatbots more often:

"Most probably I would use chatbots more in the future. If they develop and they are able to help me out more with my searches or questions, then definitely I would prefer to use a chatbot, especially when a chatbot is able to provide me with the correct and detailed information that I am looking for."

and

"I think definitely more likely especially as technology improves. I think chatbots will definitely improve. So, I think it will be a lot easier way to find information on the website instead of having to look through it myself."

and

"I think I'll be using them more often, because as they do become more advanced, they can generally give more information. The issue, at the minute, when I use chatbots for college is that they don't tend to give statistics or anything. So, as they become more developed, they should become more useful to me."

This view was also shared by the majority of PG students:

"Probably more likely, knowing me. Purely because I think they are getting better, I think they're more commonplace, more and more organisations have got them available. So that potentially increases my uses just because they are more readily available."

and

"I think we're not going to have a choice. Compare five to ten years ago with today, you pretty much never used to need to talk to a chatbot. So, the more it becomes the only way to interact with companies and try to get through, you're gonna get forced into going that way."

and

"Definitely, I would rely on it more. Yes, I'm happy to use them. I see that now more universities have chatbots. Two years ago, not many of them had. So, definitely, it's developing."

Not everyone shared this positivity and enthusiasm and some PG participants remained sceptical in view of the current status of the chatbots:

> *"I think I am going to try it and if I don't find it useful, definitely I will continue with what I'm doing now. It means that I always give a chance to myself at least to try it. But the expectation is that they are becoming more helpful."*

and

> *"I think about the same amount as I am now. Probably will try and do my own searching first before resorting to the bots. It wouldn't be the first thing that I'd click on if I'm on a website."*

When asked about the future use of chatbots, the marketing professionals attempted to imagine how the entire student recruitment process may be revolutionised by this technology. Not only would bots be part of the student journey that this research explores, but also the succeeding stages of enquiry, selection and all the way to application and admissions. Again, a spectrum of enthusiastic and sceptical views was present in the responses. Some examples include:

> *"I think that chatbots, as well as other things like it, are probably good at what we'd call 'the exploratory stage' of a student's research that may help them to shortlist institutions. And they may well shortlist based on how easy the institution has made that chat experience. But then, after a certain point, I think going to university is quite an emotive choice."*

and

> *"Previously, it was about engaging with somebody by phone call, sending them an email, perhaps arranging face-to-face appointments. And since then,*

it's taken a more three-dimensional approach where we're having video consultations with students, we are engaging with them through social media, we are now looking to incorporate chatbots as well."

and

"As they stand, I do not think bots have the potential to completely change how we recruit students. Bots can help with questions around UG open days. If you think about the student journey of when they start applying through to when you get a hit on your website, it will all be enquiries about open days, what courses, what's the admissions criteria, when and how. And for those kinds of questions, it can help with navigation, providing that you capture data and you capture details."

and

"Yeah, I have no doubt that chatbots can completely revolutionise the student recruitment journey because of the mobile phone generation. And if it can chat back to you with all the intonation and modality that you and I have, and it knows everything about the entire history of the subjects, of the teaching staff, of the faculty, of the building, of the location, and it can articulate it."

It all comes back to that need to have a human-to-human conversation when it comes to important life decisions that do not seem to be trusted to algorithms yet:

"I do think that the bot can be part of the recruitment, but I'm not sure they can be a pivotal part of it. I still think that students will always want to talk to a human."

and

> *“There are students that come to an open evening, they've looked at all the material, they've spoken to other students, but they just wanted to meet the lecturer to get a feel for what it'd be like in the teaching environment. Whether a bot could get to that stage where it could replace that rapport, that vibe or whatever it is, I'm not sure a bot could pull that off yet.”*

4.4 Discussion of Thematic Findings

This section provides a more detailed analysis of the four themes, their connections with the UTAUT2 model used as part of the theoretical framework for this research, and the interconnectedness between them. The discussion also explores the interdependence of some of the codes from one theme on choices made in relation to codes from another theme.

There are seven factors comprising UTAUT2, six of which can be directly linked to the four themes that emerged from this research. As CAs are cost free at the point of use for the student, the only factor that has not been linked here is “Price Value”. The remaining factors have a direct link to one or more of the themes as illustrated in Figure 4.4 below.

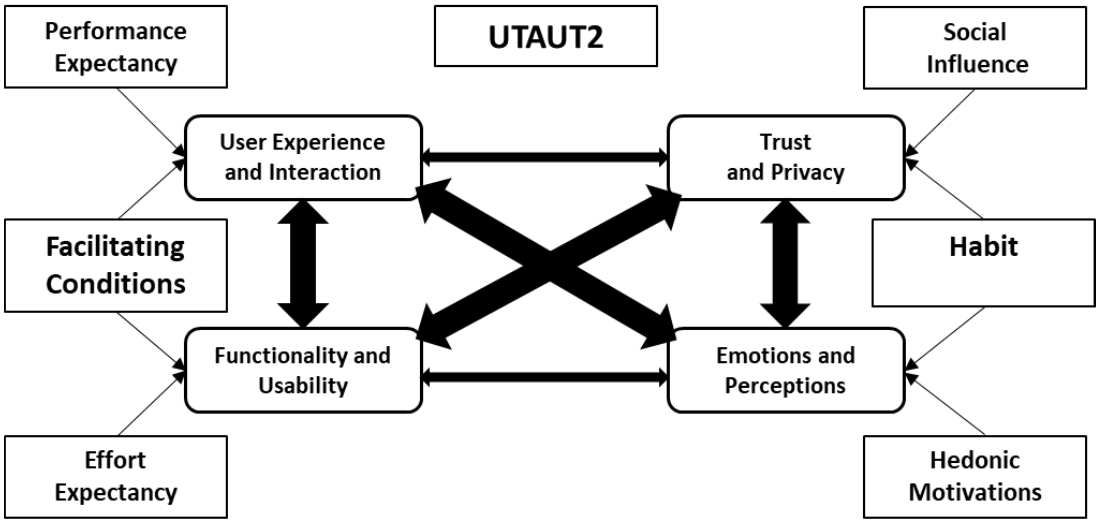

Figure 4.4 Thematic Map with Unified Theory of Acceptance and Use of Technology (UTAUT) 2 Factors (Source: Author, 2024)

The factor “performance expectancy”, or the extrinsic motivation for a user to start using and continue using a technological tool, can be directly linked to the first theme of User Experience and Interaction. In the context of CAs, performance expectancy is usually tempered by factors such as the level of development of this technology, which is still in its infancy and hence lacks attributes such as usefulness and ease of use. Many of the participants began the interaction already with expectations that the chatbots were not going to perform to high standards or provide them with the information they were looking for, whereas others had high expectations. Here are examples of some participants’ thoughts:

Two UG participants:

> *“Basically, started with low expectations that the bot will not be able to answer questions fully. I was hoping that it would provide me with some direct answers, but during the process I realised that most probably I won't get those answers directly through the chatbot.”*

and

> *"I just I don't have high expectations for the chatbot, so I don't expect much from them."*

And a PG participant:

> "*So, then I had high expectations thinking, 'Oh, this will be something good'. And then all that's happened is it's just redirected me to different pages, which is something I could have done myself."*

Even though current expectations were not very high, many of the PG participants expressed optimism about the future and their hope that the chatbots' performance would improve in time:

> *"The expectation is that in the future they are improving. The expectation is that they are becoming more helpful."*

"Facilitating conditions" is a term that describes the resources and support available to users to perform information search tasks on the chatbots as opposed to doing the search themselves using Google, the search function of the individual websites or AI generative tools such as ChatGPT or Gemini (was Bard, but renamed Gemini in 2024). Attributes such as good conversation flow or possessing the capability to remember the previous parts of a conversation can be considered facilitating conditions in this context. Providing suggestions and ideas to the user as to what type of questions may be most relevant to their personal circumstances is another facilitating condition. Participants' descriptions of good facilitating conditions were:

A Marketing professional:

> *"I do like the conversational style of ChatGPT. It does give me the feeling that I'm conversing with somebody, I'm having that kind of element of human interaction in some way because it's so conversational."*

And an UG participant:

> *"I think it's a good feature with ChatGPT because when it remembers your last conversations, it can then go back and get information and be more helpful with future questions."*

The factor of "effort expectancy" is directly linked to habit as users expect to exert less effort the more habitual a conversation with a chatbot becomes. The effort in the context of this study circles around the idea of how to ask a question so that the chatbot can understand the intended meaning of the user. This encompasses actions such as rephrasing the question when a free text chatbot was being used so that the question was worded as closely as possible to the keywords that the bot has been trained on. The effort expectancy factor was articulated by users in this way:

> *"Because I've tried twice, I've rephrased the question, and I want to see exactly a master's degree and the bot is only giving me entry requirements for undergraduate courses, I personally would go to the website."*

and

> *"I had to rephrase after copy and paste did not work. Bot, 'No problem. Please can you rephrase your question'. Yes, not really helpful. So, whatever I rephrase it to I feel that it's not picking up."*

and

“I tried to rephrase it and say just the keywords ‘undergraduate’ and ‘education’ and see if it picks up just from the keywords”.

At first sight, it might be difficult to see the link with the “social influence” factor from the UTAUT2 model, because interacting with chatbots tends to be an activity performed more often in one-to-one settings rather than in groups that offer an opportunity for social influence. However, in the context of this study, the UG participants were sometimes influenced by the opinions of their parents whom they trust when making life choices, such as selecting the right degree and institution to study. Parents are not only influencers of opinion, but a trusted confidant and often the funder of an UG degree. Therefore, CAs have the dual task to relay information appropriate for future students as well as their parents at times. One participant suggested that bots could take the following approach:

“The bot will definitely be beneficial to the parents of UG students. Perhaps if the bot asked you, ‘Are you a student?’, ‘Are you a parent?’ or ‘Are you a career advisor?’ to classify you. It can modify the type of answers.”

The factor of “habit” in the context of this research relates to an increase in the perceived ease of use of chatbots the more users are exposed to such interactions and become familiar with the functionality of their interfaces. Habituation with these conversations was expressed by participants through the attribute of normality when asked how they felt during the conversation:

“They were simple, easy to talk to. It's normal conversation with an AI.”

and

“I just find it quite normal. Most of the chatbots are doing it. They ask for the name at the beginning. They normally say your name in the first line of the

chat. Well, to be honest, I didn't even notice that. It has become quite normal now."

Habit also connects with the notion that Generation Z users are familiar with and accustomed to this type of technology and hence find it easy to use. A 17-year-old UG participant was quite relaxed about the idea of chatting with the bot having interacted with other bots previously:

> *"For me, it was easy, and I think that future students, such as my friends, they would find it quite easy because the new generation can work with chats and computers and phones more easily than other generations. So, I don't think anyone of my age will find it difficult."*

The intrinsic motivations of a user, also termed "hedonic motivations", which relate to attributes influencing the beliefs and attitudes of participants, are very closely linked with the theme of Emotional and Perceptual Aspects. Having fun and pleasure using this technology is derived from the perceptual aspects of novelty, friendliness and general ease of use, which allow participants to achieve their final goal in a frictionless and entertaining manner. A chatbot's attributes should be designed to reduce potential feelings of frustration, annoyance or irritation, because these feelings may prevent users from having a long and meaningful interaction or discourage them from using the bot again on another occasion. The "fun" factor designed into some of the bots' conversation flow was noticed by the participants:

> *"I mean, the GIFs in the one bot, they were funny. I think it makes the university seem more friendly. Yeah, more welcoming."*

and

“And this chatbot was kind of fun with the GIFs. It surprised me but very pleasantly.”

To increase the hedonic motivation of users, one marketing professional suggested:

“I'd probably prefer to do something with the bot if it made it more fun and said, ‘We're going to do a quiz!’

UTAUT2 as a model seems to closely match the results of this data analysis and provides a foundation for exploring each theme in more detail. In each of the themes, there are some concepts that the university can influence directly by making design-related decisions linked to aspects of the concept Other concepts are influenced indirectly as a result of those decisions.

4.4.1 Factors Relating to User Experience and Interaction

Understanding user experience and interaction in the context of chatbots used by HEIs for the purpose of student recruitment is a critical issue for the marketing departments of these universities. The recent popularity of ethnographic methods in the process of designing CAs has produced some remarkable results; the methods allow CA designers to combine their own technical knowledge with the needs and desires of the people who will be using the CAs (Forlizzi and Battarbee, 2004). User experiences can be quite subjective because they result from the interplay between the very objective functionality and usability of the chatbot (Theme 2) and the emotional and perceptual aspects of the individual users (Theme 4). User experiences relating to product design can be classified as physical, sensual, cognitive, emotional and aesthetic (Benaissa and Kobayashi, 2023). In the context of CAs one could argue that physical and sensual experiences are less relevant unless the CA was embodied and had a physical representation in the form of a robot answering students' questions, which is outside the scope of this study. The remaining three types of experiences are quite important in the context of students searching for information as the decision where and what to study require intense cognitive involvement and can be quite emotional, and the decision shapes the path of future careers for the students.

Earlier in the chapter, the factors under this theme were analysed under the pragmatic and hedonic categories, specifically looking through the lens of the user. Here, the factors are examined through the lens of universities and their ability to influence those factors directly or indirectly with the decisions they make about design and the desired user experiences of the prospective students (Figure 4.5).

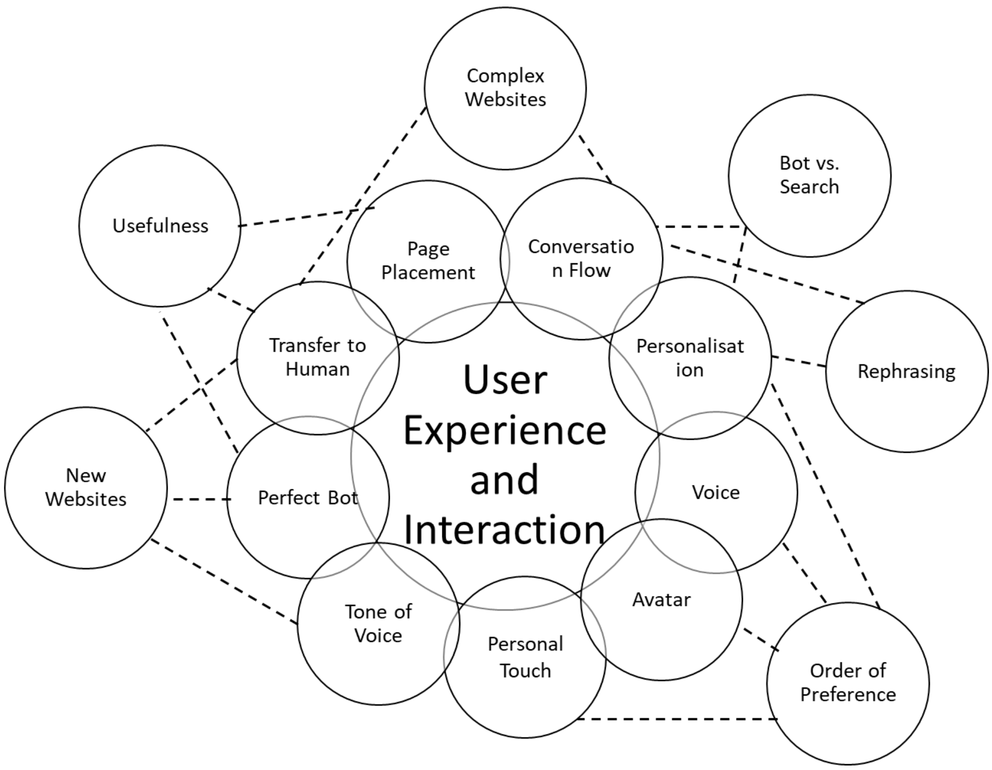

Figure 4.5 User Experience and Interaction Thematic Network Diagram (Source: Author, 2024)

The concept of usefulness is quite complex, both cognitive and emotional aspects, and can be influenced by a number of direct decisions relating to the bot. If a bot is designed to be available on every page of the website, unobtrusively available when the user wants to access it, follows the user from tab to tab as they click on links, and prompts the user if they can help further or offer the option to speak with a human, then the bot is perceived as more useful for the purpose of information gathering. If the bot had a casual, friendly and welcoming tone of voice throughout the interaction and the conversation flow reminded users of the experience when speaking to a human with reciprocal turn taking, curiosity about the student and memory of questions already asked and answered, then the user experience is rated higher by the users, the need to rephrase is reduced and students are more likely to continue with the chatbot conversation versus switching to searching for the information themselves. For many people, bots are currently not the first choice when it comes to information search. The participants saw websites as the natural first place to perform a manual search for new information; in the event that this approach did not produce satisfactory results, the participants turned their attention to the bots in the hope that they might be able to find the information faster or with more accuracy. That expectation was often dashed by subpar performance in accuracy, relevancy and speed of results or by the perception that the bot's answers lacked a component of humanity via some level of personalisation or the illusion of personal touch at a time of very emotive decision making.

Some designers try to imbue a chatbot with their own “humanness” via the creation of avatars, chatbot personalities, names and voice. These features, however, are sometimes seen to detract from the usefulness of the bot and although they are nice to have, they are not essential to the task at hand, which is to collect as much useful information as possible in the shortest time and easiest steps. Humanising features were seen by the participants as the “packaging” of the conversation, which was ranked less highly than the content of the conversation, which was seen as primary. Any features added solely for the purpose of pleasure or entertainment were only desirable if they did not detract from the substance of the conversation. Human characteristics seemed to evoke emotional reactions more associated with Theme 4 and the peripheral factors described there.

4.4.2 Factors Relating to Functionality and Usability

As is becoming clear from the analysis of the individual factors in the theme of Functionality and Usability, the two concepts are inextricably connected and interdependent. However, increasing the number of functions a system incorporates does not always increase usability. Often the perception exists that the more functions are provided to users, the greater the flexibility and complexity, which will result in greater user satisfaction and usability (Goodwin, 1987). The number of functions, according to Nickerson (1981), is only one of many factors that determines a user’s acceptance and intention to use and continue using an information system, which depends more on the usability of these functions.

Therefore, usability needs to be the primary goal when deciding on the number and type of functions a chatbot should incorporate in its design. Designing a highly usable chatbot would require a university to: understand better the intentions of the intended users; to define the purpose of the chatbot and the purpose of the conversation; and ascertain users’ level of technical and language expertise, the amount of time they expect to use the chatbot and, hence, the conversation flow that would lead to achieving users’ goals.

Some of the factors in this theme are directly under the control of the marketing departments of the universities, and others can only be influenced indirectly as depicted in Figure 4.6 below.

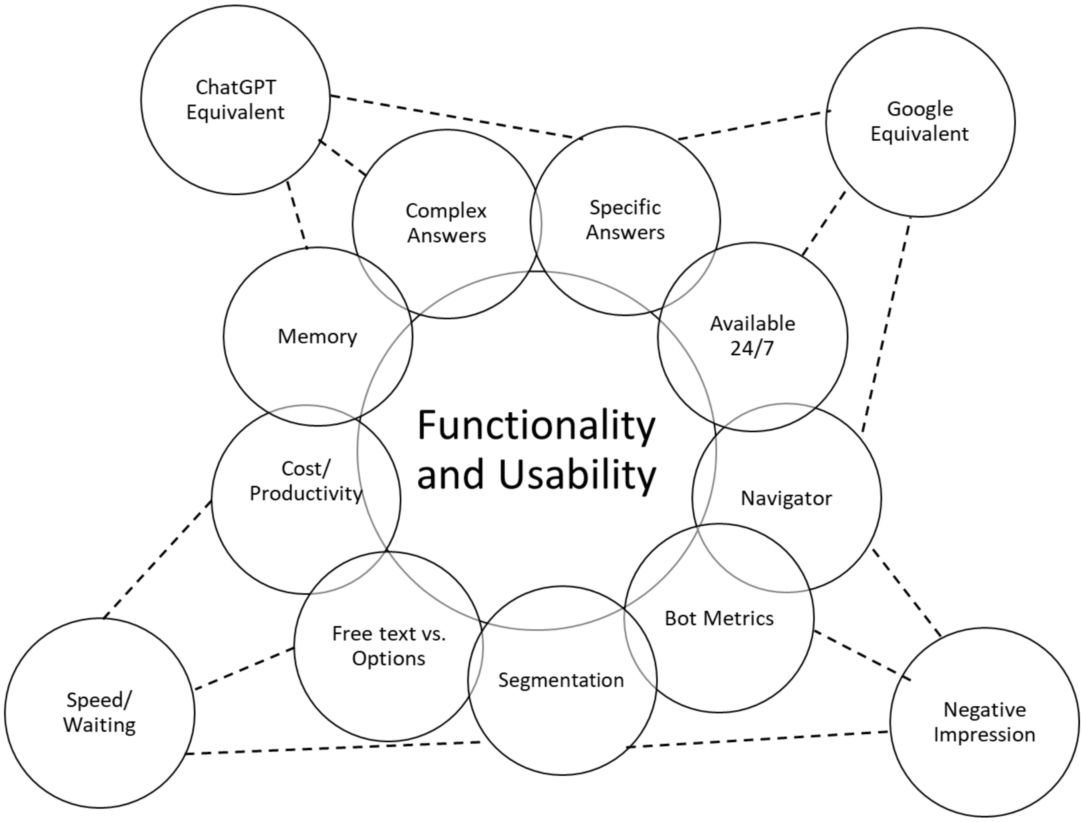

Figure 4.6 Functionality and Usability Thematic Network Diagram (Source: Author, 2024)

Universities can make the choice to invest in very sophisticated and complex knowledge databases that can power the functionality to answer complex or specific questions. The dialogue flow can be designed with the users' goals and capabilities in mind; it can either lead them to the specific answer they are looking for in relation to their specific question or offer them a quiz asking a series of questions that will create a detailed picture of the user's goals and suggest options for them to explore, especially if they are at the start of their information search journey and are unsure what specific questions to ask. These choices can indirectly influence how users interact with the bot in the instances where a website is highly information rich or has complex structures that are difficult for novice users to navigate. One of the primary findings from this research is that users wanted to have the option to have both functionalities of being able to ask a free question and to be given pre-set options. It was not a choice of either/or, but both together depending on their readiness to ask specific questions versus exploring their options at the start of the information gathering journey. In other words, they were looking for the combined functionality of being offered suggestions in the way that ChatGPT does and the option to ask a personalised question in the way we all do with Google Search. The functionality of having the ability to continue a conversation from one question to another was also inspired by what users see is possible when they interact with other generative AI tools, and that expectation is rapidly moving from being a novelty to being an expected standard functionality.

To satisfy the goals of the marketing professionals, bots should also have: highly developed functionalities around back-end reporting both on the quantity and quality of interactions, which can be used to train and improve the algorithms; the ability to segment customers into predetermined groups so that their customer journey can be customised to better meet their needs and goals; and to effectively progress a potential student through the application funnel. This in turn would indirectly influence users' desire to speed up their interaction with the university and to achieve their goals without the need to wait or queue to speak to a human agent.

4.4.3 Factors Relating to Trust and Privacy

The topic of trust in chatbots falls into the wider discussion of trust in AI in general and the notion that customers in a marketing context appear to hold AI to a higher standard than humans (Davenport et al., 2020). AI seems to be trusted less than humans when it comes to receiving information or advice from algorithms and this seems to be rooted in a belief that AI cannot feel and experience what we can as humans (Gray, 2017). Part of that attitude comes from the limited understanding of how chatbots work, and AI tools are often labelled a “black box” that churns out an answer without being able to explain how that answer was arrived at (Rai, 2020). Another part relates to the ethical choices organisations make in relation to privacy choices and handling of personal data in order to exceed customer expectations (Martin and Murphy, 2017). Both aspects of trust – lack of human feeling capability and privacy issues – can be addressed via the choices universities make when designing their CAs in relation to the attributes in the inner circle in Figure 4.7 below.

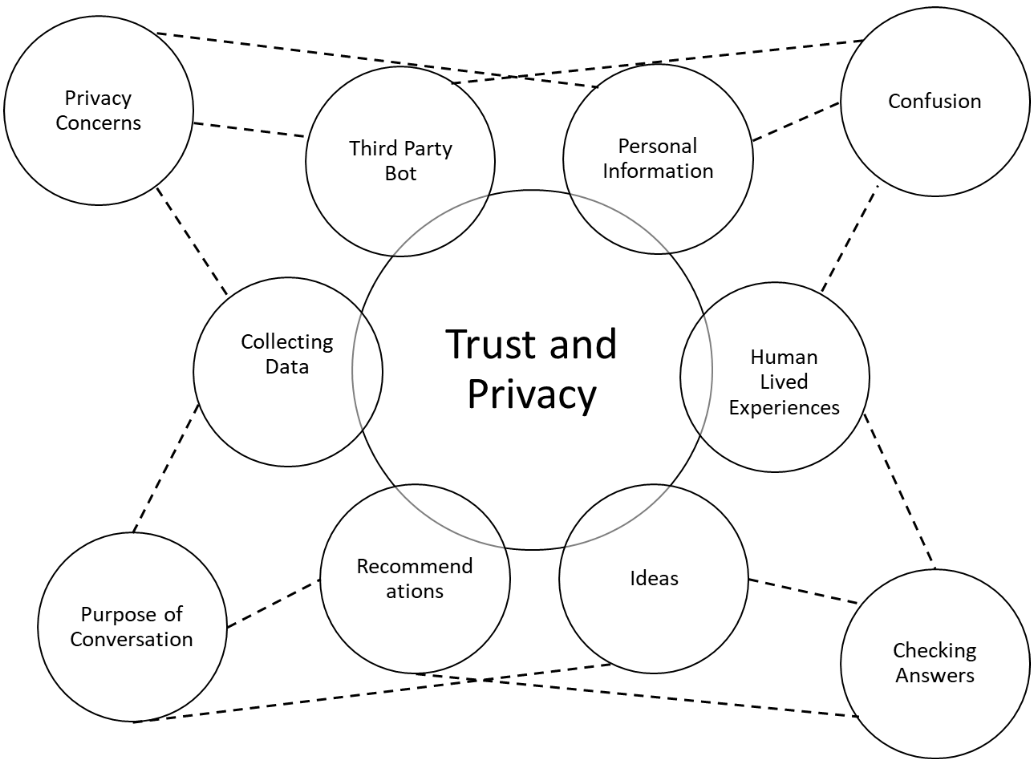

Figure 4.7 Trust and Privacy Thematic Network Diagram (Source: Author, 2024)

The interviews revealed that one of the most pertinent factors influencing the notion of trust and indirectly influencing discomfort in Theme 4 was the timing and amount of personal data collected by the bots. One university had placed the requirement to provide name, email address and country right at the start of the conversation as a gateway before a user was allowed to use the services of the chatbot. This was not perceived as positive by many of the interviewees; they saw it as a barrier to interaction and it increased their distrust in how their data would be used. Another bot did not ask for any contact information, which was also seen as a negative feature predominantly by marketing professionals who pointed out that the university would not have the option to follow up with the enquirer if they had further questions or needed further help. The most balanced approach according to the participants was when the bot provided some information and interaction, some value to the potential student and then asked for permission to collect personal information and contact them with further information.

A bot that was powered by a third-party provider also created a sense of distrust both in the university's ability to develop their own chatbot and in the way users' data would be handled. Some participants were anxious that the bots may also collect additional data on them that they did not intend to reveal, such as meta data containing their IP addresses or location.

A link between the welcome message and a sense of confusion was also evident in statements where participants were not certain if they were talking to a chatbot or to a live human agent. This confusion has a direct link to the concept of trust in the chatbot as well as in the institution behind it. Sometimes, conversations were reported to be so human-like that the participants asked whether they were conversing with a bot or a human.

The action of checking the accuracy of answers directly links with the factor in Theme 2 where accuracy and relevancy of information do not live up to the expectations of the user. If a student feels compelled to verify a bot's answer by comparing it to information from another source, then that points to a lack of trust in the abilities of the bot to perform its function and fulfil its purpose. The purpose of the chatbot and the purpose of the conversations can only be ascertained implicitly as a result of successful or disappointing interaction with the chatbot.

4.4.4 Factors Relating to Emotional and Perceptual Aspects

The act of conversing has traditionally been perceived as a very human-to-human action performed between two or more individuals for the purpose of exchanging information, sharing experiences, entertainment and expression of feelings. The conversational character of a chatbot creates similar expectations: an interaction with an algorithm should achieve similar goals of information exchange and social interaction taking into account emotional and perceptual aspects (Følstad and Brandtzaeg, 2017). Even though conversational interactions have become more commonplace in recent years, the full potential of these technologies is still not fully utilised as a result of challenges with user needs and motivations (Brandtzaeg and Følstad, 2018).

The attributes associated with this theme can also be analysed via the filter of which attributes are under the direct influence of the university and which ones can only be indirectly steered as a result of choices made. Figure 4.8 below shows an interpretation of these attributes based on the examples given in participants' statements.

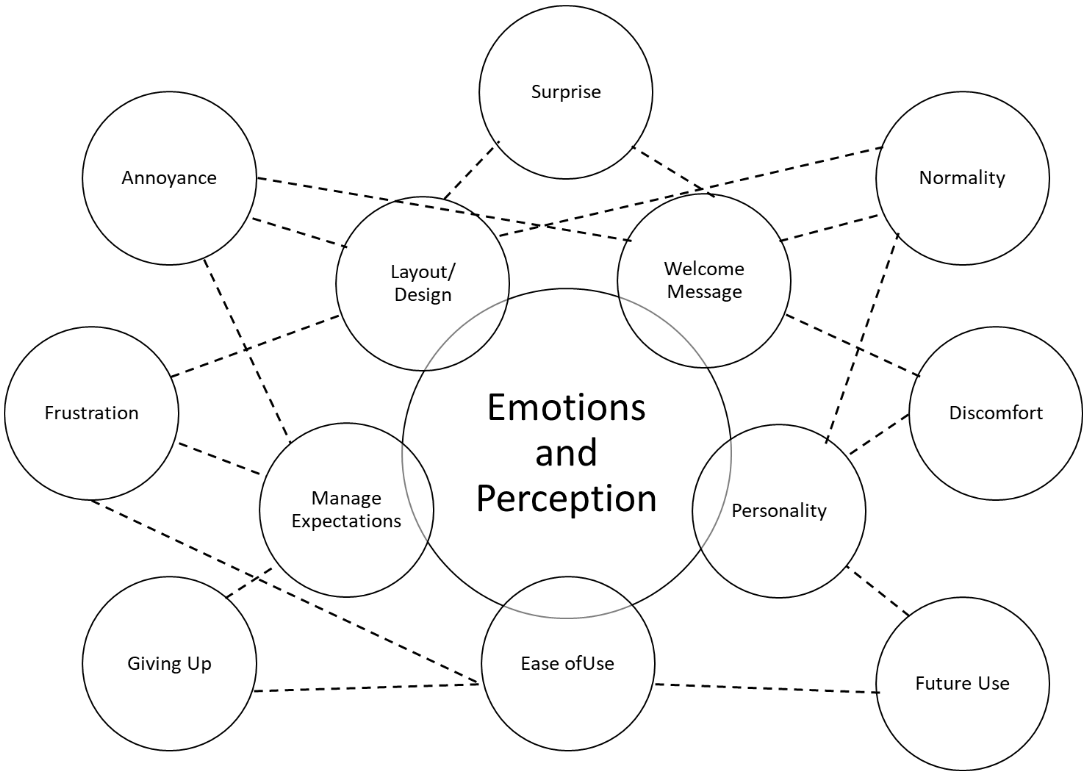

Figure 4.8 Emotional and Perceptual Aspects Thematic Network Diagram (Source: Author, 2024)

Decisions made in relation to the layout and design or the welcome message led to participants reporting that they experienced feelings of confusion as to how to use the chatbot, or annoyance with the practical difficulties in reading and assimilating the information displayed, or frustration with the obstacles they encountered in order to achieve their goal of information gathering. For example, when a welcome message was not present at all, participants were sometimes unsure how to initiate the conversation. Many of them stopped the interaction waiting to see if an instruction would appear and only continued after being prompted by the researcher. When a welcome message was very detailed and long, many of the participants ignored it altogether, did not read the information provided and began by immediately asking questions. When the welcome message was concise, the interaction was more seamless and natural, and many participants reported it to be more “conversational”.

The attribute of “personality” was linked less with initiating a conversation than with the participants’ attitude and willingness to stay engaged with the conversation. Many participants enjoyed the chatbot experience to such a degree that they kept interacting beyond the point the research required and expressed curiosity as to what might be the next stage of the conversation without being prompted. The desire to give up was greatly reduced because the entertainment factor of the conversation reduced feelings of annoyance, frustration or discomfort. This was also true for the instances when the bots issued statements at the start of the conversation declaring that they were still learning and may not be as accurate and useful as the participants would like them to be.

Similarly, the ease of use of the bots was a contributing factor to the reduced urge to give up; this indicates that as the ease of use increases so would their intention to use chatbots more in the future. Equally, the positive feelings of surprise when the bot performed well or was particularly entertaining had a reciprocal effect on feelings of discomfort or frustration.

4.5 Summary

This chapter presented an analysis and discussion of the data collected during this research utilising a chatbot experience following a semi-structured interview. The six-step thematic analysis process was discussed and its application to this research demonstrated. Then, the four themes that emerged and their respective concepts were analysed to frame the concepts that further connect them. The discussion of the findings provided clear interdependencies between the concepts; analysis was provided that linked the findings to the conceptual framework proposed in Chapter Two.

In the next chapter, the ideas from this chapter will be further developed to form a coherent conceptual framework that can be considered by HEIs developing their own approaches to using CAs as one of their marketing communication channels.

CHAPTER FIVE
CONCEPTUAL FRAMEWORK

5.1 Introduction

The foundations for this chapter were laid in Chapter Two, which provided a detailed critical review of the extant literature and identified a research gap both in the research relating to conversational AI and the research available on the student journey in the context of HE student recruitment. A theoretical framework was created on the basis of two existing models devised before the time of AI proliferation and adapted to the current status of the technology. Chapter Three justified the use of a social constructionist paradigm because it may shed a holistic light on the phenomenon of CAs that does not solely look at the positivist technical aspect or the pragmatic business perspective. The themes that emerged in the data analysis of Chapter Four highlighted the essential decisions that HEIs must make in the design and deployment of CAs guided by principles that were not evident in the existing literature.

This chapter focuses on addressing the fourth research objective and associated question, "*Which key factors and concepts identified through the previous two questions are most pertinent in the context of HEIs and the early stages of the student journey that result in a conceptual framework for decision making?".* This chapter starts with a clarification of why defining the purpose is the bedrock of any further steps in a decision-making process. Then it builds the layers of a decision framework on the design and implementation of chatbot technologies as part of HEIs' marketing communication strategies at the early stages of the student recruitment process. Firstly, the individual layers are justified in the analysis of the empirical data and then the complete conceptual framework is presented.

5.2 The Importance of Purpose

What emerges from the analysis of all four themes is that a choice made in relation to a factor in one of them has a domino effect on other factors within that theme and across themes. The running thread between all themes was revealed to be the concept of “purpose”. In the context of this research, purpose is examined through two lenses of focus: “purpose of the CA”, which is driven by the goals and objectives of the university; and “purpose of the conversation”, which is driven by the goals, needs and motivations of the potential students.

Returning to the discussion about the taxonomies of CAs in Chapter Two, this research reveals further evidence to support the points of Nißen et al. (2022) that a successful interaction between a user and a chatbot is entirely dependent on the alignment between the design features of the CAs and the various purposes and motivations of the people engaged in the conversation, including their short-, medium- and long-term goals. In the context of a HE student journey, a short-term goal may be to gather enough information on various institutions and programmes so that the prospective student is able to create a shortlist of preferred programmes and providers. A medium-term goal may be the successful completion of an application form and completing the application and enrolment process. A long-term goal may be the successful completion of the programme and graduating into employment or entrepreneurship.

Limited by the artificial narrow intelligence capabilities of today’s CAs, universities are only able to meet the students’ short-term goals when it comes to designing features and capabilities into the chatbots (Kaplan and Haenlein, 2019). With this limitation in mind, this research proposes a framework that can be applied at the design stage of a CA by a university considering AI tools to supplement and augment their marketing communications strategy and channels at the start of the holistic student journey. The proposed framework consists of four “layers” of interdependent decisions leading to the core of the framework where the design decisions are considered last after the previous three layers have been determined.

5.3 Layer One – “Purpose of Chatbot”

What is clear from the data collected is that a CA should have a very clear and narrow goal which should be communicated to the prospective users so that their expectations are managed from the start of the interaction. The warning from marketing professionals is that the bot should not try to be “all things to all people” and attempt to fulfil multiple, sometimes incompatible, goals. Here are the words of a marketing manager with over 10 years’ experience in the HE sector:

> *“It really depends on what your business goal is, and you would provide a chatbot consistent with that. You can't provide a chatbot that's going to fit everyone. It doesn't work. So be very clear with your business goal.”*

As a marketing communication tool at the start of the student journey, universities must decide what should be the primary purpose for the chatbot that is most aligned with their marketing strategy. CAs are most often expected to adopt one of the eight proposed purposes shown in Figure 5.1:

1) Knowledge base – the purpose of a knowledge-based CA is to inform and educate the user by providing information that would not be otherwise

available freely on the website or social media channels. The knowledge base may comprise a collection of blogs providing in-depth information on a particular topic or on course content, even at the level of granularity of providing a session-by-session account of workshop content. Educating the user in the very specific area of interest is dependent on creating a vast database of information that can be searched and filtered to a deep level of knowledge, which may not be available to human agents who have limited capacity and time to deal with each enquiry.

2) Question-answering tool – a CA that has been designed specifically to answer questions from users is similar in its design to the knowledge-based CAs with the major distinction that its answers can be quite succinct aiming to summarise and inform but not necessarily to educate and provide detail. The questions can either be predetermined by the university and the designers so that users can choose from a list of questions or the users can formulate their own questions using unique phraseology, which is then processed through a text classifier to determine the closest match of answers from the available information. The answers may also be predetermined and stored in an answers database or generated using natural language generation algorithms where each answer is unique to each question.

3) Perform a task – CAs that perform tasks can be designed to complete an action or sequence of actions with a predetermined goal. An example of such a CA is one that may book users onto an event such as an open day, alumni events or taster lecture for prospective students. The task needs to be narrowly defined and have a definite desired outcome within a specific timeframe. These types of CAs are quite similar to the virtual assistants we

are so accustomed to, such as Amazon Alexa and Google Home, with the exception that they usually reside on a website and do not support voice commands capabilities.

4) Navigator – these are CAs with the ultimate goal to navigate the user to a particular page on the website that contains detailed information relating to the user's question. These are the most widespread type of CAs at present, which is driven by the relatively low cost of such tools. These CAs are based on the same technology as the search bar that is present on most websites, but the interaction more closely resembles a conversation than a straightforward search. Navigator CAs are not designed to simplify or summarise data in the way a question-answering CA might do and may simply provide a link to a page without much explanation why that link is deemed the most relevant and appropriate for the question asked.
5) Quiz – the questionnaire type of CA is more often found at the end of a customer experience where organisations are looking for feedback from the customers and evaluation of the service provided. The conversation flow in these types of CAs is reversed where the questions are not being asked by the user but by the CA and the user is the one that provides the answers. At the start of the student journey, this type of CA can be designed in a way that prospective students are asked questions about their interests, predicted grades, desired career direction and so on. Depending on the answers provided, the CA can list results of matches that most closely align with the answers of the students and historical data from past students' and alumni's outcomes.

6) Lead generation – CAs whose primary purpose is to generate leads for the marketing departments of HEIs are designed with the intention to collect as much information as possible in the most secure way possible. Organisations whose strategy is commercially driven, such as private universities, tend to utilise multiple marketing channels specifically for the purpose of lead generation. An investment in a CA would most likely be evaluated in the number of leads generated as one of its success metrics followed by the quality of such leads that would convert into application, enrolments and, eventually, students at a rate that is compared to the rate of human agents performing similar tasks. Lead generation CAs would usually start with questions relating to collection of personal data before allowing the user to progress with the conversation.
7) Recommendation – this type of AI technology was popularised by entertainment companies, such as Netflix and Amazon, where an algorithm begins with recommendation of popular choices made by other users. Through interaction the algorithm gradually targets more narrowly the recommendations to the preferences of each individual user having learned a few pieces of information about them through the choices they make. In the context of HEIs, this CA may start by recommending the most popular programmes they offer and, over time, tailor those recommendations as it learns more about the user’s motivations, goals and preferences. These CAs can also work in reverse where the user may start with a very specific enquiry about a course and the CA may present additional information to suggest related or similar products, and auxiliary information that the user may have not asked yet or not know that is relevant.

8) Entertainment – a CA whose primary purpose is to entertain is rarely seen in the context of HEIs. They are more prevalent in social interactions designed to provide emotional responses and satisfaction. However, this goal may be designed as a secondary purpose in a CA that is primarily aimed at providing a recommendation or administering a questionnaire. This purpose is primarily achieved via the hedonic attributes discussed earlier, where factors designed to elicit an emotional reaction of pleasant surprise, feeling of friendliness and casual tone of voice are used sometimes in combination, in addition to providing information to the user.

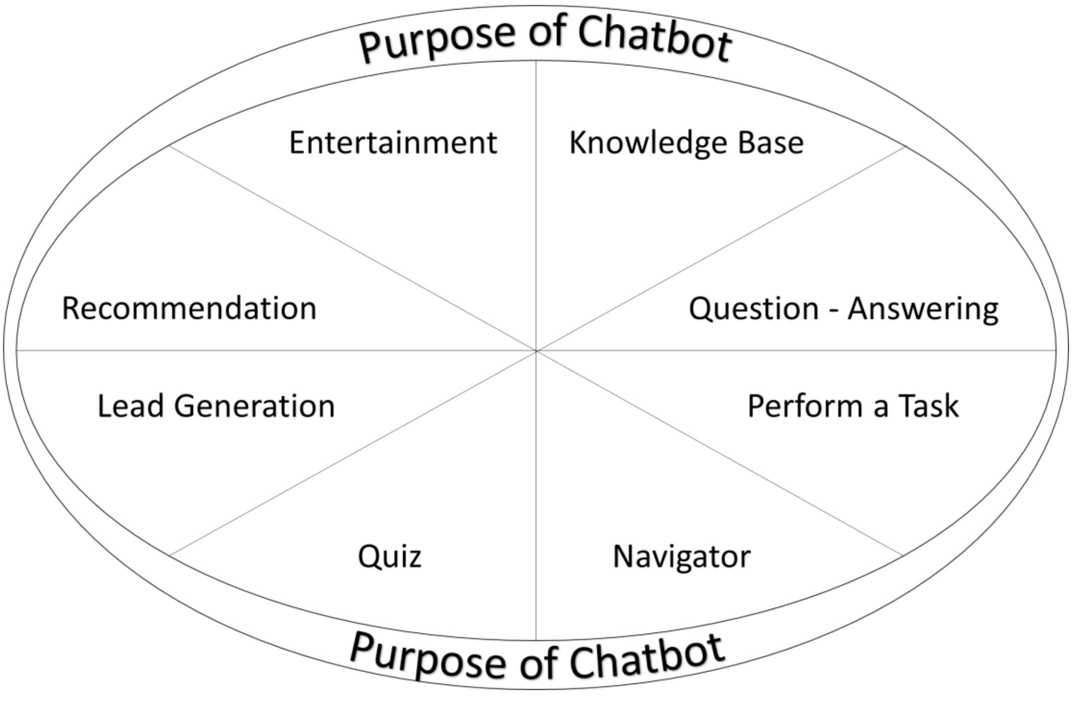

Figure 5.1. Conceptual Framework – Layer 1 – Purpose of Chatbot (Source: Author, 2024)

Some of these purposes can complement each other, while others can be completely mutually exclusive. For example, a knowledge-based CA can also be combined with a question-answering CA, or a quiz CA can also provide entertainment, while a lead generation CA would usually fail and disappoint users if combined with one aimed to entertain, educate or navigate. Therefore, a clear purpose of the chatbot must be determined taking into account a university's commercial strategy, marketing strategy and communications strategy.

Once the purpose of the chatbot has been identified by the HEI, a deeper dive is needed to determine the purpose of the conversation between the institution and the user.

5.4 Layer Two – "Purpose of Conversation"

Once the purpose of the CA has been decided, either as a singular aim or a primary purpose supported by a secondary purpose, the HEI should establish the short-term goals and motivations of the potential users. The various purposes of the conversation from users' perspectives can be analysed through the lens of the ELM and UTAUT2 proposed in the theoretical framework for this research. Choosing where and what to study at university is likely to be considered using the central route, or a cognitive-based process, which requires cognitive resources, a high level of motivation and a high level of ability to absorb, analyse and accept information, concepts and ideas. Therefore, it is expected that conversations with a chatbot will follow the central route in most cases. It is not expected that potential users will use the university chatbots primarily for entertainment or social purposes, because of the implications of making the right decision that can shape their future career. The research results indicated, however, that both routes were being used depending on where the users were in their information gathering journey. This analysis led to the definition of four distinct purposes of users who choose to initiate a conversation with a CA as shown in Figure 5.2:

1) Discover new information – users at the very start of their journey, still considering a wide range of options and gathering initial information about their potential choices, seemed to employ the peripheral route more than the central route. This is the stage where the participants did not see the conversation with a bot to have very high stakes in relation to their final decision. The interaction tended to be more open-minded, playful and accepting of hedonic attributes such as quizzes, GIFs and funny remarks used in the language. This type of information is well served by CAs whose purpose is to entertain, quiz, recommend or navigate.
2) Conversation experience – users in the same stage of information gathering (i.e., right at the start of the student journey) may also engage with a CA to try to initiate a conversation in order to gauge the HEI's culture and approach to its students. The conversation experience with a CA can give clues as to whether the institution values professionalism, academic rigour and a "no-nonsense" approach to education or if it is the kind of institution that values personal experiences, growth and holistic well-being for their students. These kinds of hedonic judgements are usually derived from speaking with university representatives, visiting the university, open days and so on. The CA, being a digital representative of the university, can also deliver the same message to potential students and their parents if the HEI has designed the CA with that purpose in mind.
3) Confirm existing information – further down the student journey, participants usually arrive at the chatbot conversation already having gathered a lot of information and wanting either validation of the assumptions they had or were looking for answers to their personalised questions. They tend to display

many of the characteristics of the central route over the peripheral route where cognitive effort was applied routinely while interacting with the CAs. At the same time less attention was paid to the affective-based processes and users relied less on the heuristic cues around layout, anthropomorphism and personality of the bots. When users arrive with preconceived ideas either about the HEI or the programme of study, the conversation is expected to be conducted as quickly as possible without distractions or unnecessary steps that prevent the user from reaching their final goal. CAs with the purpose to navigate, perform a task or answer questions are most aligned with the goals and motivations of these CA users.

4) Action or process – users at this stage of the journey may also want to go a step further and not just gather and confirm information, but actually perform an action relating to that information. For example, they may be interested in speaking with a human agent who can answer very specific and individual questions that the CA has not been trained to handle; therefore, they might request to be transferred to the relevant person who will take them through the remainder of the process. Another possible use case may be a booking for a specific event, taster lecture or open day when the user is ready to invest more time and effort into a particular institution to validate any information or choices that are being considered. The CA that performs an action on behalf of the user may one day have the capability to take the users through to the next stage of the student journey and assist prospective students complete their application, enrolment and induction. However, this may only be possible if a number of CAs seamlessly hand over the user from one to another or

when artificial narrow intelligence may evolve to the next stage of artificial general intelligence.

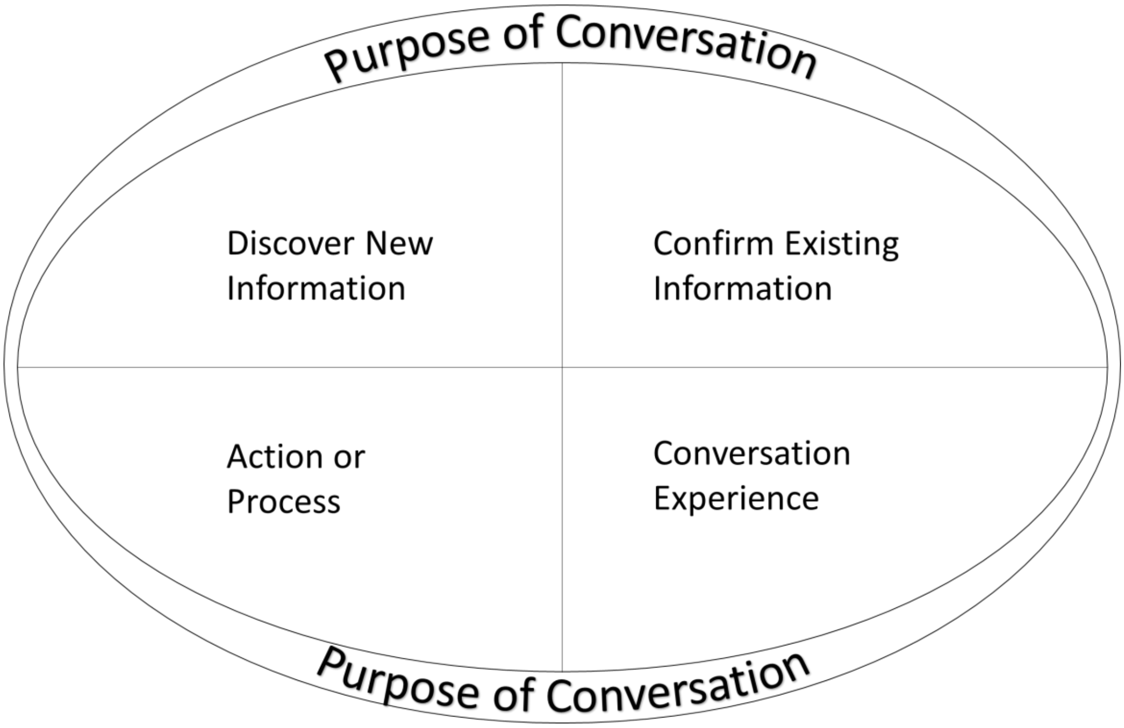

Figure 5.2. Conceptual Framework – Layer 2 – Purpose of Conversation (Source: Author, 2024)

One participant summarised this layer of the framework perfectly:

> *"If I have a really clear goal of what I want to know from a bot, then I'm probably there."*

Once the purpose of the CA and the purpose of the conversation have been aligned, the next step is to pay attention to what groups of users might be attempting to interact with the HEI. This is the purpose of the third layer of the framework.

5.5 Layer Three – "Type of User"

The previous layer proposed four conversation purposes and alluded to the fact that these purposes may be connected to the level of existing knowledge in the user.

This level of knowledge informs two of the four user types proposed for this framework. It has transpired from the empirical data that the intended users for a university CA in most cases are going to be prospective students at various stages of the student journey. However, there are other individuals with a vested interest in the process who may also turn to a CA for information and assistance with enquiries about courses or with the aim to perform a task. To be able to truly design a user experience that provides satisfaction alongside achieving a goal, the HEI must understand the evolving goals and motivations of each user type. This framework proposes the definition of four user types most likely to choose to interact with a university CA summarised in Figure 5.3:

1) Students with little or no prior information – potential students at the very start of their information gathering journey, whether searching for UG, PG or doctoral programme, have a different mindset to information gathering, typically being quite curious and looking to explore, to learn and to compare available options, even if they do not seem a close match to their original preconceptions. These users employ their curiosity to discover new information through reading blogs, student reviews and course pages, or they take quizzes, and they are open to be entertained. Any opinions formed or decisions taken at this stage are of low stakes that may or may not have a bearing on their final decision. These users are unlikely to commit to a more time-consuming or involved communication with the university in the form of events, open days or spending time talking to an agent. They are also unlikely to see the necessity to share their personal information as that may signal a stronger interest in the institution than intended. Knowledge-based,

entertainment, quiz and recommendation CAs are the most suitable CAs for this type of user.

2) Students with some information – once initial impressions have been gathered and some opinions formed, users tend to become more practical in their search and continue gathering information to either fill the gaps in their knowledge or to confirm already collected information. These users are looking for speed in their interactions; they are less likely to pay attention to heuristic cues and less likely to seek exploration or entertainment. At the same time, they are more likely to use the central route of absorbing and analysing persuasive information, more likely to share their personal information to signal a stronger interest in what the HEI has to offer and more likely to seek ways to perform actions such as ask to be transferred to a human agent or book spaces on an open day. This user group would be best served by a navigator, task performer, lead generation or question-answering CA.
3) Parents or guardians – another group of potential users with a vested interest in collecting and evaluating information on university programmes is the parents and guardians of potential students, especially those that may travel abroad to study as international students. Not only are parents likely to carry some or all of the financial burden of completing a HE degree, but they may also be very involved in the future careers of their children, as is customary in some cultures. Parents and guardians may also engage with a CA with little or no prior information on the courses available or the university or they may require clarification on already obtained facts. There is, however, a difference in the approaches utilised by this user group, which is less likely to be

interested in the culture of the HEI or the entertainment experienced while gathering information, while looking for hedonic signs of credibility, professionalism and prestige. This is usually achieved with a more serious and impersonal tone of voice, which is somewhat in contrast with the friendly and casual tone of voice expected by potential students looking for a cultural fit. This group of users would most likely be best served by a navigator or question-answering CA as well as a task-oriented CA to aid in their aim to speak to a human agent.

4) Career advisors – another group of users with a vested interest in the successful placement of potential students with the most appropriate programme or university are professionals, such as career guidance councillors, who advise secondary level or university students on the next steps of their student journey or career. While they possess a good amount of information on universities and programmes, they are also likely to use the CAs to update or confirm existing information or to book students onto university events and open days. These users are also unlikely to seek the entertainment factor in the communication experience and regard CAs as a tool for achieving their goals in a faster and more efficient way than pursuing contact with a human agent via phone or email. Similarly to parents and students with some information, speed and efficiency of communication would be a driving factor and aim of the CA interaction.

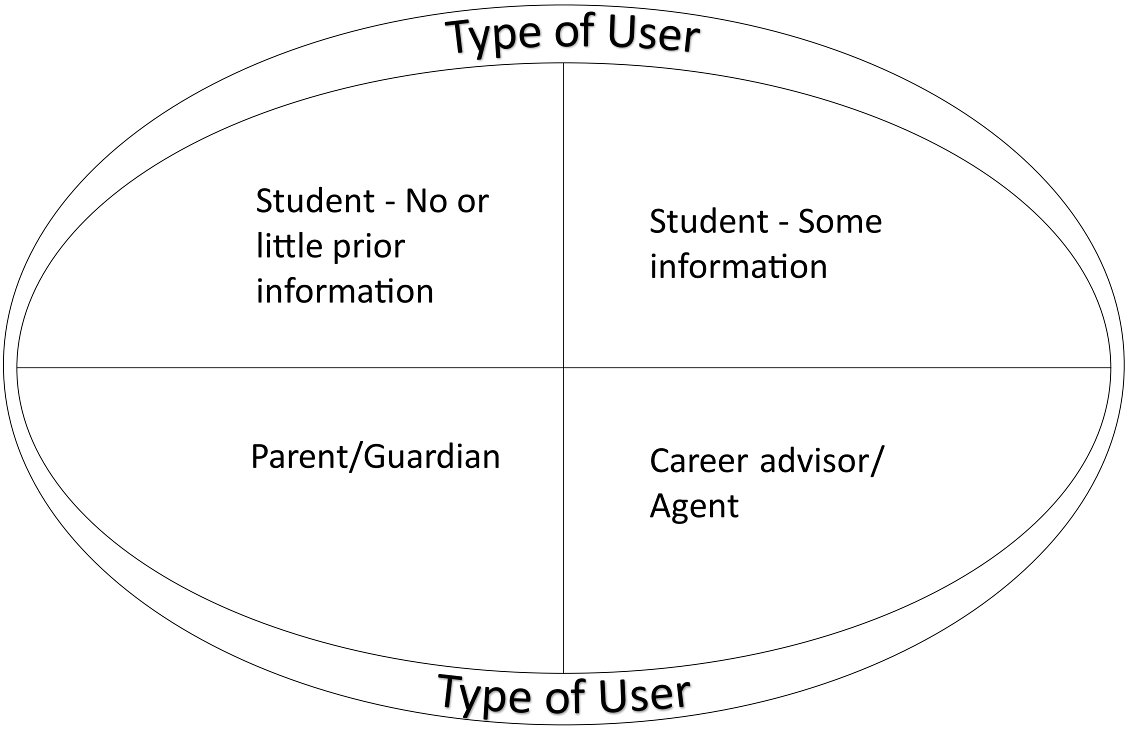

Figure 5.3. Conceptual Framework – Layer 3 – Type of User (Source: Author, 2024)

A user group not included in this framework is students who are already existing students at the university. This was a deliberate decision based on the data collected during the interviews. Many of the participants from both the students' groups and from the marketing professionals' group were surprised to see an option to select a status of existing student. The prevailing opinion was that existing students would be unlikely to use the website to seek for information relevant to them as websites are considered a marketing tool to attract potential students. The second reason quoted was that existing students are usually given access to a university's internal portal or intranet that is specifically designed to cater to the needs of existing students. Even though some of the CAs offered the option to support enquiries from existing students, the participants saw that as unnecessary and redundant.

When decisions have been made in relation to choices in this third layer of the framework, HEIs can finally move to the final layer and the core of the decision-making process around the individual design features of their CA.

5.6 Layer Four – "Decisions"

The inner most layer of the framework can be reached after the outer layers have been analysed through the lens of the organisational and marketing communication strategy of the individual HEI. At this level, the four themes that emerged from this research can be addressed considering the environment in which the CA is expected to operate as demonstrated in Figure 5.4. As described in the previous chapter, each of the themes comprises topics that can either be directly influenced by the HEI and hence become decisions for the institution to make, invest and commit to, or factors that the university will seek to indirectly influence by those decisions. Some combinations of decisions are complementary to each other, whereas others are mutually exclusive. The list of decisions proposed in this framework is not exhaustive and is directly derived from the research data as the most pertinent decisions making a difference to the potential users of the CA. Some of the attributes highlighted in the interviews were desired by all respondents and certain features were deemed necessary regardless of what stage of the student journey the user was on or the type of user interacting. For example, features such as always having the option to speak to a human, being available 24/7, and always having the option to either type free text or click on pre-set options were seen as essential requirements for a successful conversation outcome. Another feature that emerged during comparisons with generative AI tools, such as Open AI's ChatGPT and Google's Gemini, was the ability to hold a longer conversation through the use of good conversation flow aided by memory that allowed for the building of ever more specific and complex questions and answers. The ever-increasing popularity of these tools and the wider exposure of the population to their strengths are raising the bar of users' expectations. Having experienced a personalised, friendly conversation flow elsewhere, users are aware of the capabilities of chatbot technology at any given time and expect that these capabilities can be replicated in HEI chatbots. This expectation is further fuelled by the perception that HEIs should be equipped to educate the designers of the future and therefore they need to be at the forefront of the latest developments and functionality.

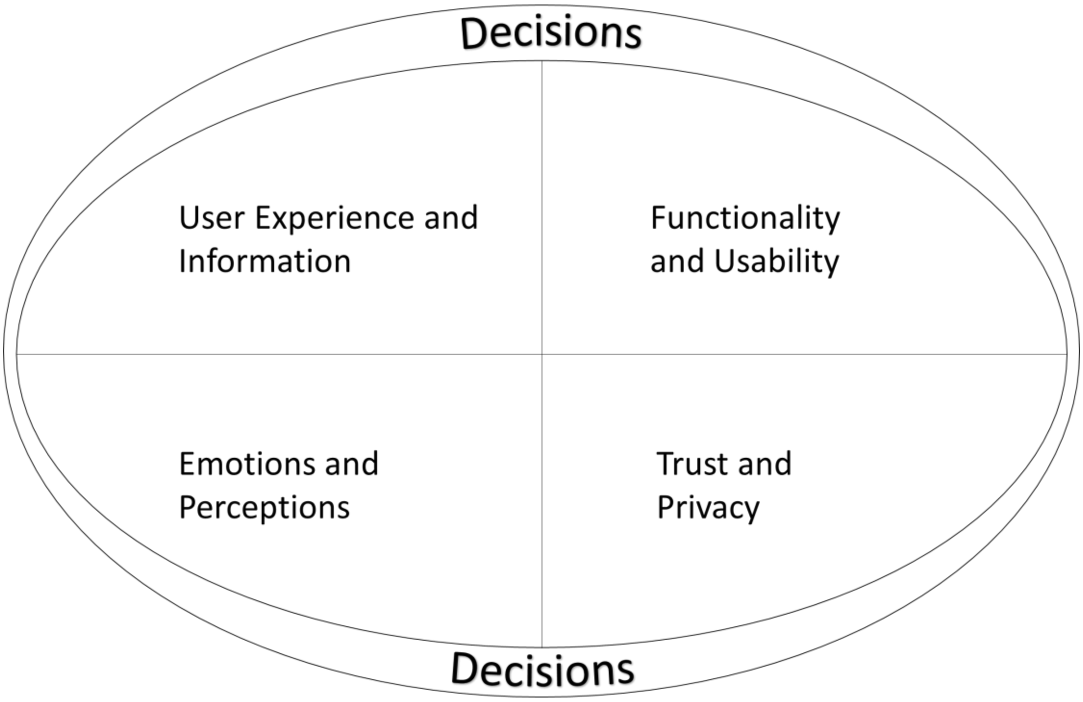

Figure 5.4. Conceptual Framework – Layer 4 – Decisions (Source: Author, 2024)

Each of these decisions may lie along a spectrum rather than being a binary decision. Some specific examples linked to the type of user are discussed below.

1) Students with no or little prior information – if the CA has been designed to serve this category of users, then the purpose of the conversation would most likely be to discover new information or have a conversation experience. Therefore, the features the CA should possess from the user experience category would be a friendly and casual tone of voice; avatar and voice interfaces can be helpful to demonstrate the institutional culture in the same way a tone of voice sends peripheral cues to the user about the type of organisation they are interacting with. Furthermore, there should be an opportunity to personalise the conversation through the CA asking for the name of the user, but not necessarily for other personal information because that could lead to distrust in the intention of the CA. The CA should be placed on the home page and follow the conversation through to further tabs as the user explores the website and available information. There should always be an option to record the conversation and make it available for later retrieval or to transfer it to a human agent should the user wish to take the conversation further.

   The functionality of the CA for this group should include predetermined questions and options as students in this category may not yet know what the important questions are they should be asking. Instead, a very guided journey throughout the conversation or the website should be designed with prompts about the next step to consider. From a marketing perspective, this CA could initiate the conversation linking it to the last page the user visited and thus further customising and personalising the conversation to the interests of each user.

The layout needs to be intuitive with a more detailed welcome message giving information and instructions to manage the expectations of the users prior to engaging in a conversation. Asking clarification questions from the user to get to know them better as well as tailor the response to their specific circumstances is a desired feature for this user. However, at the same time offering other options to consider is appreciated as the users are still unsure of exactly what they are looking for.

2) Students with some information – it is very likely that this group of users has explored a number of websites and perhaps even interacted with various CAs in their information search journey. This user type is looking for efficiency, effectiveness and speed in the interaction. The purpose of the conversation is likely to be to confirm existing information or to perform a particular action or process. Being more informed about the available options, these users are more likely to leave their personal information to be contacted back by the institution and be less concerned about data privacy issues having seen similar trends across the sector. They are also more likely to look for functionality where the chatbot would allow them to ask their own specific and complex questions in an attempt to filter the general information to the level of more specific and personalised interaction; in this scenario, the bot is seen as an alternative to speaking with a human due to its potential speed and availability. These users are less interested in avatars, lengthy welcome messages, segmentation questions or many options to click on before they are allowed to customise their user experience and information to meet their needs and motivations for the interaction. The capability to remember previous parts of the conversation and excellent conversation flow are critical

for the successful outcome of such CA interactions. The closer this interaction comes to the experience of speaking with a human agent, including the assurance that the needs of the user are truly understood, the more likely it is that the CA will be considered a credible channel of communication and the information provided as trusted and reliable for making life-altering decisions by the student.

3) Parent or guardian – this group of users may resemble either of the two user groups above in terms of their level of knowledge and information, however, they differ considerably from the students searching for themselves as other factors may play an important role in the final decision beyond what the students consider appropriate. Parents, for example, may be additionally concerned with accommodation costs and conditions available at the institution, they may consider the range of clubs and societies as important as the content of the courses studied, or they may consider alumni profiles and employability prospects as a deciding factor for selecting one institution above another. When designing CAs that cater for this user type it may be prudent to provide as many options as possible at the start with a very strong segmentation questionnaire to really understand the goals and motivations of the individual user. The tone of voice must be appropriate for a more mature audience that is making judgements and forming first impressions that can be based on the choice of language used by the CA. The welcome message must be comprehensive enough to provide alternatives if the channel is not meeting the users' expectations. The option to be transferred to a human agent is even more pertinent for this type of user who tends to want to receive confirmation of the information gathered thus far as well as confirmation that

their impressions and conclusions are shared amongst other parents. The entertainment and heuristic features may be of less importance to this group due to the general understanding that when investing large amounts of money in the future of their dependents, parents and guardians see the information gathering stage as critical to get right due to its long-term implications and impact on the future of the student.

4) Career advisors and agents – similar to parents and guardians, this group of users is performing information gathering on behalf of someone else where the final decision does not affect them personally but may affect them professionally. This group of users is perhaps the most objective user group with the least amount of emotional attachment to the final decision and the one that is least interested in the conversation experience or entertainment factor built into the conversation. Efficiency and speed are driving factors for choosing the CA over the alternative of speaking to or emailing human agents; therefore, a succinct welcome message with short answers pointing the user where to go for more information if they wish to do so may be most appropriate in this case. Expressions of humanness, such as personality, avatar and voice interaction, are often seen as unnecessary and indulgent, sometimes detracting from efficiency and effectiveness that are seen as more valuable. Career advisors or agents often act as an intermediary between the student and the institution; therefore, they often provide that human-lived experience that students seek which seems lacking when they engage with CAs directly. Therefore, CAs need to be factual, perform specific tasks faster and easier than a human can on their own, and carefully manage the

expectations of where its abilities may be limited by clearly indicating what is and what is not within their scope.

Figure 5.5 below summarises the discussion in this section.

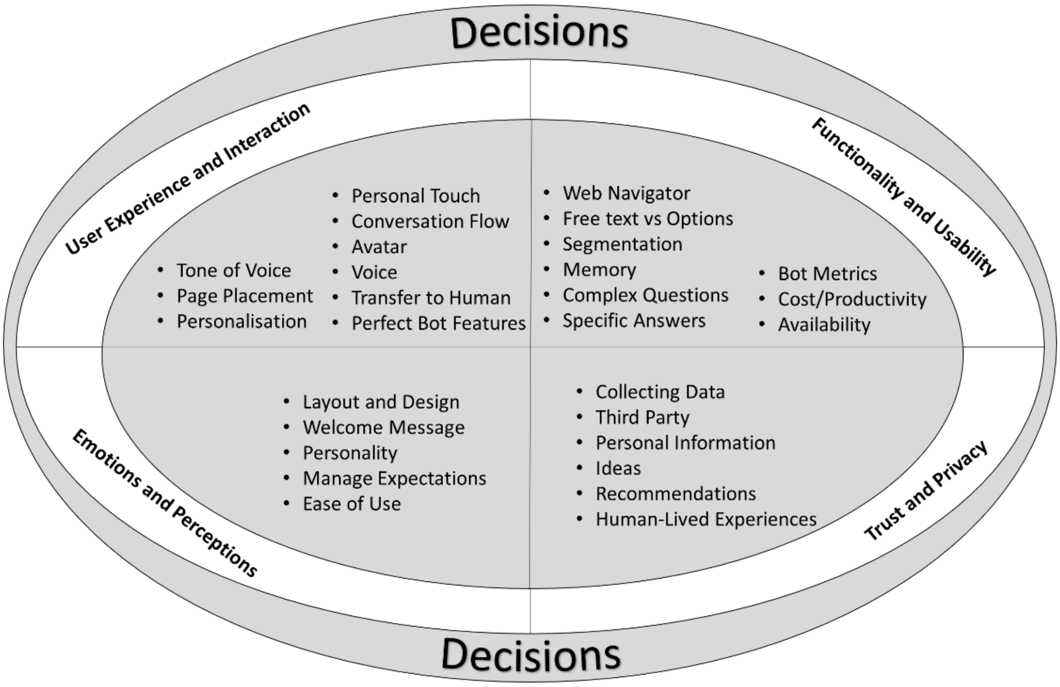

Figure 5.5. Conceptual Framework – Inner layer (Source: Author, 2024)

5.7 The Conceptual Framework

This study conceptualises the effectiveness of CAs in the HEI student journey as a four-layer decision-making process starting from the outer later and progressing to the core. This framework provides the answer to the fourth research question: "*Which key concepts identified through the previous two questions are most pertinent in the context of HEIs and the early stages of the student journey that result in a conceptual framework for decision making?"*

The framework also provides a direct answer to the research challenges posed by Putoni et al. (2021) and Følstad et al. (2021) detailed in the rationale for this study.

Answering Følstad et al.'s (2021) first research direction to gather up-to-date knowledge on a wide range of chatbot users and user groups and the implications of their chatbot use, this framework provides deep knowledge of the user groups identified in layer three: students, their parents or guardians and the professionals that support students in their decisions. Layer three differentiates the users not by demographic factors but by the specific purpose for the interaction with the chatbots and provides insights to marketing professionals of the impact their design choices may have on these specific groups.

The second research direction about chatbot user experiences and design concerns was directly answered by the fourth layer of the framework where the themes of 'User Experience and Interaction', 'Functionality and Usability', 'Trust and Privacy' and 'Emotional and Perceptual Aspects' provide insights as to how design decisions can directly and indirectly influence the users' motivations, perceptions and responses. This study undertakes a user-centred approach to evaluating the pragmatic experiences, where CAs are tested to determine if they help the users achieve their information search goals, and the hedonic experiences, where CAs manage the users' expectations and provide a satisfactory emotional response to the human–AI interaction.

This layer of the framework also provides answers to Puntoni et al.'s (2021) call for research into the AI capabilities of: "listening", that is, gathering user data for the purpose of segmenting and for better understanding of user type; "predicting" and "producing", that is, understanding a user's enquiry and constructing an appropriate answer; and “interacting”, that is, communicating with the user meeting their pragmatic and hedonic goals.

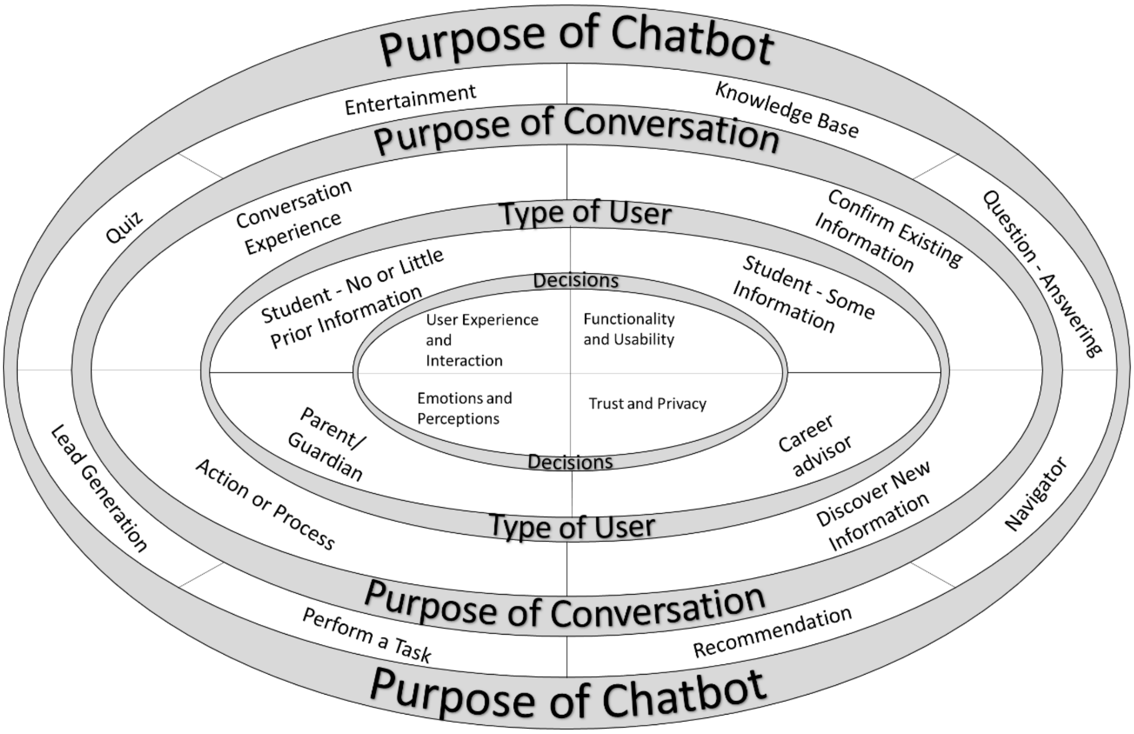

Figure 5.6. Conceptual Framework (Source: Author, 2024)

Figure 5.6 illustrates that when all four layers of the framework are combined, they become a powerful tool for marketing professionals in HEIs; a tool that can guide the decision-making process to reach the most successful outcome and the best return on investment for the institution. The empirical evidence strongly suggests that the purpose of the CA must be determined first at a strategic level and be aligned with the overall university strategy and what would be the ultimate measure of success that will justify the investment. If the university aims to simply lighten the load of human agents, perhaps a question-answering or knowledge-based CA would be most appropriate. If the aim would be to progress an enquiry quickly and efficiently down the recruitment channel, then perhaps lead generation or a task-oriented CA would be suitable. If, however, the university wishes to communicate its values, personality and build long-term relationships, perhaps a CA with more of an entertainment focus, or a recommendation or quiz type CA, may be chosen.

Once the outer layer of the model has been determined, the next layer of the model focuses on the needs and goals of the users. By considering the purpose of the conversation from users' perspective, the HEI will be assessing the purpose of the CA from both perspectives ensuring they are aligned as closely as possible. Market research and user testing at this stage may be needed to ensure there is evidence of the assumptions underpinning the decisions. The CA's purpose and design will differ depending on whether the data reveal that the users are seeking to discover more about the institution and the programmes having landed on the website with little prior knowledge, or the data reveal that the users might be searching for information around the website by themselves for a considerable time before engaging with the CA. Heatmaps and page visits on the website tracking may reveal patterns of information search that will indicate the stage at which the users may be prior to engaging in a conversation.

The data will inevitably reveal the type of user most likely to engage in a conversation, which will further inform the design features that can be built and made prominent early in the interaction. The primary users need to be identified so that their needs and aims can be catered to in a more comprehensive way and in this way contribute towards the university's strategic goals. All design decisions can be grouped under one of the four themes identified and specific metrics can be designed to measure their effectiveness from a marketing and organisational perspective.

The four layers of the framework are interdependent in so far as a decision at any one of the layers has a domino effect on the preceding and succeeding layer as well as the final outcome for the user and the university. This interdependence makes the framework even more critical because it can highlight the impact of each individual decision and its influence on the entire ecosystem of decisions.

5.8 Summary

This chapter conceptualised the meaning of purpose from the HEI’s and users’ perspective. It then presented the conceptual framework derived from the empirical evidence gathered for this research and analysed in Chapter Four. It presented details of each of the four layers of the framework and a path for decision making starting from the outer layer and working towards the centre. The framework is positioned to represent a design tool to aid marketing professionals and HEIs in general in their decision-making process.

CHAPTER SIX
CONCLUSIONS AND RECOMMENDATIONS

6.1 Introduction

The previous chapter presented the contribution of this research to the extant knowledge about CAs in the context of marketing communication by HEIs at the start of the student journey. The contribution resulted in the development of a conceptual framework based on the empirical data collected in the course of this research. This chapter presents an evaluation of the findings in the form of conclusions linked back to the research objectives, as well as recommendations that result from the discussion thus far. The Contributions to Theory section (Section 6.3) presents direct and concrete answers to calls for future research detailed in the research rationale (Section 1.5). Managerial implications of applying the framework in the current HEI environment are discussed and address both strategic and operational implications. Issues of transferability of the findings of the study are examined and solutions suggested. The chapter also provides recommendations on how researchers can build upon the concepts identified here in future studies.

6.2 Evaluation of Findings

The aim of this research study was defined in early 2021 when the landscape of AI, conversational AI and CAs was very different from the reality in 2024 when the study was concluded. At the start of the research process, the majority of the population was not familiar with the concept of CAs or chatbots, and the terminologies used in this topic were unknown to many consumers. In the three-year period of developing this research topic, CAs have been adopted by many more organisations in various industries, many more consumers have been exposed to the technology and interacted with it, and the launch of ChatGPT in November 2022 democratised access to LLMs and their capabilities. The researcher's professional background in HE marketing and experience in launching chatbot technologies provided validity to the aim of this research, which was to explore the effectiveness of CAs in the marketing communications strategies of HEIs with a specific focus on how the student journey is affected in light of these technologies. This aim was supported by four objectives that explored the subject from both theoretical and empirical perspectives.

Under the first objective, theoretical underpinnings were explored in the existing literature. Conceptualising what is meant by the terms AI and conversational AI was not an easy task considering the rapid developments in this field and ever-moving goalposts when trying to define the phenomenon. While Crawford (2021, p.7) asserted that AI is "neither artificial, nor intelligent" and Fortuna and Gorbaniuk (2022) labelled AI as being both fashionable and ambiguous, scholars like Dreyfus (1972) and Bostrom (2017) quoting John McCarthy, one of the fathers of modern AI, were convinced that these definitions would continue to evolve; their views were summarised in the notorious expression, "As soon as it works, no one calls it AI anymore" (Bostrom, 2017, p.14). Conversational AI, a more recent phenomenon emerging strongly in 2016, was conceptualised as a subset of AI that was concerned predominantly with the task of bridging the barrier between humans and machines through the use of language. A taxonomy of CAs was presented as a way of laying the foundations of the current state of understanding and classifying this technology, and as a tool to define the current meaning of CAs which are the focus of this study.

When exploring the extant literature for evidence of marketing approaches affecting the student journey, a distinctive feature emerged time and time again where the start of the student journey began at the start of the student's study time and concluded at the end of their course. This study conceptualises that the student journey should be viewed as a more holistic process starting much earlier with the initial information search and decisions made during the time individuals select their courses and HEI to study. A "holistic student journey" is the foundation used for the analysis in this study, which encompasses not only the time spent at a particular institution but also the time before, including student recruitment activities and application process, and the time after when students gain alumnus status.

The exploration of the extant literature did not reveal substantial existing knowledge in the application of CAs in the student recruitment campaigns of HEIs and this revealed a gap for exploration where new empirical data would provide valuable new insights into the phenomenon of interest. Two relevant theories were selected to provide a lens for analysis of the newly collected data that would help provide theoretical contributions to the knowledge in this subject.

The second and the third objectives of this research applied an empirical perspective on the topic and were concerned with gathering rich data. Some data were collected by observing the participants interact with existing CAs and evaluating CAs' effectiveness in aiding potential students along their student journey, and other data were collected from in-depth, semi-structured interviews that explored factors that may influence HRI and improve the student experience in the process. Originally, three groups of participants were selected to explore the potential differences that may exist between UG and graduate students and to triangulate their views with the views of the HEIs behind the CA technologies by interviewing marketing professionals. The empirical data revealed that there were no significant differences between students searching for UG or PG programmes, however, a different classification emerged, namely between students with no prior knowledge of the programme or institution and students with some prior knowledge. In the process of being interviewed, the students and marketing professionals also revealed two further groups that may be using the CA technologies; these were the parents or guardians of students, and career advisors or agents with a professional interest in the student recruitment process. The effectiveness of CAs would be considered completely differently by each of the identified groups depending on their goals and motivations for using the technology. The factors that would lead to successful HRI or a long-term relationship with the HEI would also greatly differ from group to group dependent on the purpose of each user group.

The findings from the empirical data revealed the emergence of four major themes that form the core of the conceptual framework. Objective four set out to develop such a framework that could be used in further research of the phenomenon or provide a basis for practical implementation in the cases where HEIs are considering the launch of a CA in their own student recruitment marketing campaigns. The framework provides a structured decision-making process where organisations need to crystalise the purpose of launching a CA in the first place and link it to a wider strategic goal for that institution. Then, questions must be answered about the purpose of the conversations prospective users may want to engage in with a CA, which will lead to an easier identification of the user groups that a CA is likely to be effective for. Only then can the individual decisions around user experience, functionality, trust and perceptions be aligned for a more successful interaction and building of long-term relationships.

6.3 Contributions to Theory

This study identifies a conceptual link between IMC as a strategic approach of organisations and AI’s ability to enhance an organisation's benefits on three levels. AI tools can enhance efficiency at the tactical or campaign level by replacing time-consuming and labour-consuming processes of customer data analysis. At the cross-functional level, algorithms can provide coordination between channels and platforms based on customer insights to increase the effectiveness of campaigns. On a strategic level, predictive analytics can analyse historic customer data in a holistic way and provide predictions that can inform strategic decisions on the brand’s communication with its customers.

This study also identifies a research gap in the extant literature on conversational AI at the intercept between research on marketing communications focusing on customer engagement in mostly short-term purchasing transactions, such as e-commerce situations, and the research on the student experience predominantly from the view of pedagogical tasks. This research examines users’ interactions with CAs in situations where a more considered and expensive purchase is made in the context of choosing a degree to study that may last between one and four years and it explores a part of the student journey mostly excluded from research on topics of student journey in HE.

A major theoretical contribution of this research study is the definition of the holistic student journey, which extends the existing concept of student journey to include the student recruitment process that comprises four stages: awareness, evaluation, application and enrolment. The study explores the adoption of CAs in that first stage of a student journey when awareness may be limited or patchy and then evaluation, which may be taking place with incomplete data. CAs have the potential to not only provide the necessary information to the prospective students in an easy, accessible and timely manner, but also to portray other peripheral cues that may aid the decision-making process, such as institution culture and character.

Puntoni et al.'s (2021) study was chosen as the foundation for the rationale of this research as it recognises the transformative trend in marketing where computer science shapes organisational culture and how marketing operates. AI-powered tools are being rapidly adopted for the sake of efficiency and accuracy (Green and Viljoen, 2020); however, Puntoni et al. (2021) focused their attention on the context and social implications of AI tools for the individuals interacting with them. Focusing just on the technical capabilities of CAs and failing to incorporate behavioural insights into the application of these tools may undermine their effectiveness as in the case of student recruitment campaigns by HEIs. The customer-centric view of AI in this study bridges the gap between the technological considerations, namely AI's capabilities of "listening", "judgement" and "output systems", and the consumer benefits these tools provide and how those capabilities are experienced by customers. This research offers answers to the questions of how potential students engage with the activities of "data capture", "classification" and "social experience" and how that affects the student journey.

In marketing activities and CRM, issues with data capture are often centred on ethical concerns, especially in the context of persuasive conversations (Belk, 2021; Labrecque et al., 2024) and bias in the datasets used to train AI algorithms (Akter et al., 2021; Nazer et al., 2023). Data capture is usually undertaken for the purpose of improving personalisation of marketing strategies and may consist of not just explicitly collected data, such as demographic data, but also covertly collected meta data, such as location, browsing history, purchase history and even psychographic data; this is done in the name of creating customer profiles and predicting future behaviour (Cloarec, 2022; Chan-Olmsted, Chen and Kim, 2024). In the conceptual framework of this research, data capture activities feature prominently in decisions relating to Theme 3, which is “Trust and Privacy”, as well as Theme 4, which “Emotional and Perceptual Aspects”. Choices about when to ask for personal data and what type of personal data is appropriate for the conversation are at the heart of the conceptual framework defined in Chapter five.

Puntoni et al.’s (2021) “classification activities” assert a link between an organisation’s ability to personalise the customer experience with the activity of defining user groups and segmenting them into specific types. Classification experiences can be perceived as positive in the instances where customers feel deeply understood, either objectively or subjectively, and being associated with a specific group may be perceived as advantageous (Fritze, Völckner and Melnyk, 2024). Equally, classification experiences may lead consumers to feel misunderstood, which would lead to perceptions of mistrust in the AI algorithm and its ability to provide relevant information, as seen in some of the accounts of participants in this research. In the conceptual framework of this research, Layer Three provides specific insights into how classification can improve the effectiveness of CAs in the specific context of HEIs. In this instance, classification activities form the basis of which user group is interacting with the CA and what should be the conversation flow that follows based on the correct identification of the user type.

The “social experience” aspect of Puntoni et al.’s (2021) framework specifically examines the relationships brands build with their customers using AI tools while aiming for that relationship to feel as natural and as human-like as possible. This aim is achieved through the incorporation of certain features, such as avatars, friendly tone of voice and humour (Blut et al., 2021). Appealing to customers' emotions and perceptions of the AI tools reduces feelings of mistrust and fosters the beginning of a meaningful relationship and longer-term interaction (Lajante, Tojib and Ho, 2023). A meaningful social experience with an AI tool can be beneficial in the instances where efficiency is paramount for the customer or when the alternative is no interaction at all, such as website browsing out of working hours (Lim et al., 2022). In the conceptual framework of this research, social experience activities capture the choices made relating to the first and second themes of “User Experience and Interaction” and “Functionality and Usability” comprising decisions related to the second and third objective of this research study. In the context of HEIs, social experience has a very specific meaning determined by the user type, user intentions and the purpose of the conversation. These are aspects of the social experience not previously defined in extant research.

The conceptual framework in this study also addresses directions for further research proposed by Følstad et al. (2021) and their call for interdisciplinary research on chatbot development and application to provide a basis for broader discussion on the future of the technology. From the six directions for future research, this study aligns with the first two, namely “users and implications” and “chatbot user experience and design”. The definitions of specific user groups, their characteristics, goals and motivations, and external conditions for choosing to engage with a chatbot are still under-researched in many situations and use cases. This study provides empirical evidence to precisely answer these types of questions; it defines four distinct user groups and their goals, motivations and antecedents for chatbot use. These user groups, relating specifically to the student recruitment process in HEIs, are quite distinct from other use cases in other industries where the relationships between the customer, their parents and recruitment professionals do not exist in such an interdependent way. This positions the research to address questions about CA use not just as an individual but also as a group and potentially as society at large.

The direction to explore user experience and design is reflected at the core of the conceptual framework produced by this research. The four themes of this research provide specific empirical evidence to address questions of: how users perceive and respond to chatbots; how specific decisions pertaining to layout and design may influence the user experience; and how interaction mechanisms, conversation flow and conversation content should be designed to meet and potentially exceed customer expectations. This research provides insights as to how chatbot design may contribute to increased trust and satisfaction amongst users and how perceptions and emotions can be influenced by the design choices of structure, colours, shapes and fonts. Augmenting both pragmatic and hedonic characteristics in the design can produce radically different results for the various user groups identified in this context.

Drawing on ELM and UTAUT2, this research provides clear links between the two models that facilitated the development of the conceptual framework (Figure 2.4). The first main link labelled as “motivation” appears in two factors of UTAUT2 that represent pragmatic and hedonic chatbot characteristics, namely “performance expectancy” and “hedonic motivations”. The connection that can be observed in ELM is whether the user has high or low motivation, which leads to either the central or peripheral route when evaluating persuasive information. In the context of a student journey, it is highly likely that the chatbot users are predominantly using the central route as they possess high levels of motivation and have high performance expectancy while secondary hedonic motivations are secondary. The second link of “social influence” is clearly connected with the “social influence” factor in UTAUT2 and represents the peripheral route of ELM where heuristic cues influence the chatbot experience either through the presence of parents or career advisors in the decision-making process. Selecting a university course is almost never a decision taken in isolation without consulting with others in the immediate social circle of the individual; hence, these decisions can be viewed as socially influenced. The third link of “ability” connects the central route of ELM where ability is high with the personal resources and skills of “facilitating conditions” in UTAUT2. In the context of an information search, the ability of the users is usually high considering their willingness to search for information themselves before resorting to using a CA. Therefore, we can infer that CA users usually have high ability and personal resources to conduct the interaction.

6.4 Managerial Contributions

This research study provides practical insights into the design and launch of chatbots used for student recruitment. Five key areas have been identified where the conceptual framework can bring tangible benefits to the decision-making process of HEIs: strategic planning and implementation, marketing communications strategy, people skills, organisational processes and financial implications. Each of these areas is explored further below.

The overall organisational strategy must reflect the institution's desire to adopt and develop AI and conversational AI tools across the organisation. Developments in AI drive the emergence of new business models and reveal new competitive advantages not possible without the adoption of these new technologies (Perifanis and Kitsios, 2023). To successfully develop and deploy conversational AI tools, the overall organisational strategy must be agile and flexible enough to respond in a timely manner to the fast-paced developments in the field. For that purpose, "organisational ambidexterity" is necessary so that AI tools can support a strategic focus on both routine and innovative uses of CAs (Chakma, Paul and Dhir, 2021). In 2024, CAs for most HEIs would constitute innovative applications that require a creative, emergent and inventive strategy, which will drive further innovations in work processes, people skills and customer experience. A few years down the road is when HEIs may see CAs as a routine part of their operations and being widely used on a regular basis across various use cases. Only then may HEIs see standardisation across work processes, an increase in productivity and a reduction in costs. The simultaneous adoption of both approaches, or AI ambidexterity, will enable HEIs to capitalise on established and tested technologies while exploring new opportunities in the environment for real-time solutions to challenges and issues. Therefore, decisions linked to the outer layer of the conceptual framework directly correlate with the strategic direction the organisation is selecting to pursue.

Following from the overall strategic implications of adopting AI tools in the student recruitment initiatives of HEIs, these decisions also have policy implications for the organisation. As universities seek to enhance their competitive advantage and attract students more effectively to their courses, they will inevitably have to make decisions around personalisation, predictive analytics and automated processes, which will need to be regulated and made transparent to users. These decisions raise policy considerations around data privacy, ethical use of AI and regulatory compliance. When considering data privacy and security, UK HEIs are constrained by UK GDPR and other local data protection laws from the territories where data are collected. From an ethical perspective, HEIs would need to ensure that their automation and prediction algorithms are trained on good quality datasets, that the information provided via CAs is transparent and the recommendations are not based on biased assumptions. HEIs must also contend with the evolving regulatory and compliance frameworks related to the use of AI for decision making, especially in the admissions processes. The new EU AI Act, for example, also has an impact on how UK HEIs operate, as its influence on the UK National AI Strategy sets a high bar for protecting personal rights and freedoms.

Organisational strategies should also inform marketing strategies and specifically the mix of communication channels appropriate for the audience. The addition of another communication channel, such as a conversational AI tool, must be carefully integrated in the communications strategy of each HEI so that the message being communicated is not diluted or augmented; despite its technical limitations, the story about the institution that the new AI tool delivers should be as clear and as compelling as the story told by all other channels (Senyapar, 2024). The implications for marketing professionals would be driven by the correct choices made when defining the second layer of the conceptual framework. Once the purpose of the CA has been established by the organisational strategy, marketing-related decisions will link directly with decisions relating to the purpose of the CA and the user groups that would be best targeted with these CAs. These decisions have a direct impact on the third layer of the framework as the purpose of conversation and types of users are so closely linked as evidenced by the empirical data presented here. For marketing communication through CAs to be successful, there must be congruence between the nature of the message, the type of user and the medium of communication so that the needs and expectations of the potential customer can be anticipated and met effectively (Eagle et al., 2020).

The decision by HEIs to deploy a CA in their student journey by applying the conceptual framework would require them to recognise and develop different sets of skills in the people employed in marketing and student agent roles. One of the potential benefits of deploying a CA on the website of a university is that frequently asked and repeated questions can be answered by the conversational AI tool, which gives human agents more time and capacity to deal with more specific and complex enquiries that require flexibility when applying the rules and the demonstration of real empathy when dealing with emotional issues. This shift in focus from the mundane and operational tasks, which may currently fill an agent's workday, to the more relational, emotional and perceptual aspect of communication, which currently evade the skills of CAs, may also need to be developed in the human agents. The second set of skills that emerges from this collaborative work between human agents and CAs is the technical capabilities to monitor and control the output of CAs so that they learn from their conversations with potential students and improve the accuracy and relevancy of the answers they provide. If a CA tool is launched without a process of ongoing training and improvement embedded in the tasks of marketing departments, then these AI tools will very quickly become less adept at the task for which they were designed and the benefits to customers will reduce over time.

Connected to the previous point of people skills, is the impact that the adoption of CAs will have on organisational processes. Well-developed AI tools that have a clearly defined purpose and correctly identified user group have the potential to not only provide a personalised and targeted user experience but also to perform tasks and processes that would have been ordinarily performed by human agents. When a work process is either augmented or shortened it provides opportunities for HEIs to realise productivity gains where human agents can become more efficient in resolving more customer issues or close more applications; in addition, human agents might feel greater job satisfaction when repetitive and boring administrative tasks are removed and replaced with more interesting rewarding ones that bring a greater feeling of accomplishment. Increased productivity and a more satisfied workforce are the prerequisites for realising cost savings by accelerating customer service interactions and having a more motivated workforce (Carter and Knol, 2020). Another impact on organisational processes is the addition of the new expectation that the CAs need a regular cycle of review, training and improvement if they are to remain a good return on investment for the organisation. In the same way human agents undergo regular cycles of training and skill development efforts, CAs should also have a routine process of absorbing new data, which would allow them to improve their performance over time and become even more valuable as alternative communication channels to prospective students.

Finally, we must not ignore the financial implications of deploying conversational AI tools in HEIs. Depending on the platform of choice, the desired capabilities and range of functionalities, CAs can demand a substantial capital outlay from the start. The costs are usually associated with: purchasing or building the algorithm that will power the CA; obtaining, cleaning and preparing the training data; the creation of the knowledge base that will be used by the CA; the time and staff to pre-train the CA, including several rounds of testing. This type of marketing investment can be quite large if the HEI is looking to develop an AI tool that will be effective from the start and be able to meet or exceed prospective students' expectations. There is a second consideration in relation to financial costs and that is the ongoing maintenance and training of the CA. This second wave of costs is sometimes ignored or forgotten by organisations, which is detrimental to the successful adoption of CAs by students and the continued effectiveness of the tool over time. Financial considerations are sometimes the reason why adoption amongst HEIs may be slow. However, with the introduction of generative AI tools such as ChatGPT, Claude and Gemini, the underlying LLM models have become increasingly more affordable; this this may soon help remove the financial barrier many organisations feel is preventing them from beginning the journey of adoption.

6.5 Limitations of the Study

This study examined the topic of incorporating CAs in the IMC of HEIs in the UK only. To ensure a level of transferability to organisations in similar circumstances, this research gathered information of users' interactions with CAs and rich data from semi-structured interviews containing a wide range of contextual data. These rich data may or may not be sufficient to provide HEIs in other parts of the world with the confidence to make their own judgement as to how applicable the findings in the study might be to their own circumstances. The conceptual framework was developed on the basis of the empirical evidence; it sets out a decision-making process that makes connections back to the organisational strategy, the marketing communications strategy, the user groups and their goals and motivations for interacting with a chatbot. These strategic plans would vary considerably in different macro and microenvironments driven by socio-economic, technological and political considerations.

The transferability of the study may also be limited due to the omission of quantitative data. Having made the conscious choice not to collect quantitative data at the research design stage of the project, the aim of this study was more focused on the lived experiences of the participants rather than looking to validate the extent to which attitudes and beliefs are shared between the groups or to seek any kind of correlation between the variables. This is also the reason this study did not attempt a demographic data analysis. For valid conclusions about the results from a particular age group, a much larger sample would be needed to justify any statistical inferences. If, in addition to the semi-structured interviews, surveys with multiple choice or Likert scale questions were deployed, then the findings of the study may have increased transferability to a wider set of circumstances than the ones explored in this study.

During the data collection stage 6, CAs were shortlisted for the task-based part of the interview and representatives from the different chatbot frameworks were chosen to bring variety to the chatbot experience by having a mixture of decision trees, free text and AI frameworks. The study did not, however, seek to make comparison between the frameworks and did not look to establish differences based on the type of CA used. This research design decision was taken at the start of the process as very few participants would be deeply familiar with framework differences, unless they were engaged in the task of designing a CA, and therefore would not be able to make a valid evaluation of the different types presented to them.

Similarly, this study did not seek to establish differences in attitudes, beliefs and values based on either the hardware or software platforms. The chatbot experience was carried out on a web browser. There may be differences in both the ease of use and functionality if conversations are carried out on a mobile device where the interface is much smaller and the design parameters are very different. Equally, there was no attempt to compare the CAs linked to HE websites to the ones deployed on social media pages, which often operate on different frameworks and databases. Considering that the first free commercial chatbots were launched on Facebook in 2016, it might have been revealing to expose participants to both CAs of the same organisation and attempt to detect differences in attitudes.

The cross-sectional time horizon of this study captures a snapshot in both the state of development of CA technology and in a particular step of the student journey. This study does not capture new capabilities of AI tools, which may overcome some of the limitations of the technology discussed. In addition, CAs may have a long-term impact on student outcomes. It is possible that students who used CAs in their student recruitment stage might achieve different results at graduation compared to their colleagues who did not, as they would have been confident and capable to engage with the CA technology from the start of their journey and be open to its use throughout their course of study.

6.6 Future Research Directions

This study adopted a social constructionist research paradigm utilising a qualitative methodology and narrative enquiry method to extract rich data from semi-structured interviews that can be triangulated amongst three different types of participants. This ensured the research quality concepts of trustworthiness, transferability, dependability and confirmability were observed and justified (Denzin and Lincoln, 2011). However, for future research there may be value in exploring the topic from a quantitative perspective or mixed methods approach where a larger number of CAs can be tested for their effectiveness and a larger number of participants can attempt a conversation experience that can be both quantified and qualified. Furthermore, a quantitative study may provide insights into the relative weight of the individual factors and potentially reveal correlational relationships using statistical analysis.

Furthermore, this study only explored CAs that were available through desktop versions of the websites of UK-based universities. Websites usually have mobile versions which sometimes differ in functionality from the desktop versions. Only one of the interview participants in this study explored the CA’s functionality on a mobile version of the website and made some interesting observations. Future studies may focus on the user experience and functionality of chatbots accessed via mobile devices and provide empirical data that could be compared to data gathered in this research. Similarities and differences between the different modalities may reveal interesting insights into users’ goals, motivations and outcomes.

In addition, desktop or mobile websites are not the only platforms that support CAs as many organisations chose to launch them on social media platforms, WhatsApp or cross-platforms, which allows for the conversation to follow the user across devices and channels. A further study on CAs by HEIs on other platforms may reveal insights and concepts that could not be captured by the single platform approach of this study.

To further increase the transferability of this research, future studies could explore CAs from other countries outside the UK. Not only might these CAs employ a different primary language of communication but they might also reflect the cultural characteristics of the potential users expressed in the choices made in relation to layout, tone of voice and other heuristic cues. In the US, for example, where wider acceptance of CAs as well as larger investments in the technology's capabilities have been observed, future studies may be able to develop the conceptual framework further with additional decisions to be made about functionality or user experience.

On a wider scale, this conceptual framework may also be applied to other industries and situations where a considered purchase is being made and a long deliberation process occurs prior to committing to a product or an organisation that may have a critical impact on the lives of customers. This framework can be adapted to large purchasing decisions, such as real estate or a car (two major decisions people tend to make in their lifetime). The framework can retain the layers and order of the decisions; however, the details of the individual choices will be adapted to the specificity of those situations.

Another avenue that further studies could explore leads from the limitation that this study was cross-sectional in its time horizon. A longitudinal study of the topic may be able to capture current trends more accurately and predict the speed and rate of change in both technology and users' motivations and goals. This study defined the "holistic student journey" as encompassing all the stages from student recruitment through to the status of alumnus. A longitudinal study may be able to follow individuals as they progress through the student journey and gain insights into any potential correlation between choices made at the start of the journey, such as to use or not use a CA, and student outcomes at the end of the journey.

This study presents data and a conceptual framework that address two of the six research directions proposed by Følstad et al. (2021). Two further topics, namely “chatbot framework and platforms” and “ethics and privacy in chatbots” were only superficially discussed in this research to provide context to the discussion. Future research could adopt a more technical approach to chatbot design and development and provide insights into questions relating to HRI factors as well as technical specifications around the platforms and frameworks used for development. A prototype CA could be built to test the characteristics of the conceptual framework. Ethical considerations and the application of ethical policies, such as the recent EU AI Act (European Parliament, 2023), can be explored in the context of HEIs and the user groups identified, including under 18s and the protections they have.

The rapid development of generative AI tools and LLMs and the increasing use of generative AI tools and LLMs to power CAs in various industries and use cases needs further exploration, specifically in the context of the limitations current NLU chatbots exhibit as demonstrated in the empirical data of this research. There is strong initial evidence that many of the factors leading to disappointment in the participants can be overcome if the underlying technology harnesses the powers of generative AI tools for the specific purpose of student recruitment. Future studies may be able to demonstrate how a CA’s functionality may meet and even exceed users’ expectations considering the superior technical capabilities of LLMs.

Finally, this study triangulated the results between UG and PG students and the perspective of the HEIs through the views of the marketing professionals. The other two user groups identified in the framework, namely the parent or guardian groups and the career advisor or agent group were not included in this study. This was due to the fact that these two potential user groups were not initially obvious to the researcher until the data were collected and insights emerged during the thematic analysis and conceptualisation stages of the research.

6.7 Summary

This chapter presented the conclusion and recommendations of this study. From the starting point of identifying the research gap, and defining the knowledge contribution this research brings, this study set out to explore and gather data on a new phenomenon driven by the fast-paced developments in the space of conversational AI. The empirical findings were evaluated in relation to their significance and relevance to the four objectives of the research, and the theoretical and empirical approach to the topic was highlighted. The four themes that emerged from the data form the core of the conceptual framework set out in Chapter Five, which provides both theoretical contributions as well as practical implications. The theoretical contribution of both empirical data and the theoretical framework brings new insights and clarity to the application of chatbots in the under-researched field of HE student recruitment. The study also identified five areas of managerial implications that need to be considered by organisations applying the conceptual framework in real-life scenarios. The chapter also provided directions for further research that can build on the presented findings and test the data and the framework quantitatively or in the context of other similar use cases. This study confidently met the aim and objectives it set out to achieve and provides a foundation for future researchers on the topic to build future studies reflecting the rapidly evolving state of the AI phenomenon.

REFERENCES

Adadi, A. and Berrada, M., 2018. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE access*, *6*, pp.52138-52160.

Adler, E., 2002. Constructivism in International Relations. In Handbook of International Relations, edited by Carlsnaes, W., Risse, T. and Simmons, B., Thousand Oaks: Sage.

Adwan, A., 2024. Can companies in digital marketing benefit from artificial intelligence in content creation?. *International Journal of Data and Network Science*, *8*(2), pp.797-808.

Agarwal, S. and Linh, N.T.D., 2021. A Study of Student's Subjective Well-Being Through Chatbot in Higher Education. In *Further Advances in Internet of Things in Biomedical and Cyber Physical Systems*, pp. 383-403. Springer, Cham.

Ageron, B., Bentahar, O., & Gunasekaran, A., 2020. Digital supply chain: challenges and future directions. *Supply Chain Forum: An International Journal, 21*(3), pp. 133-138.

Agrawal, A., Gans, J. and Goldfarb, A., 2018. *Prediction machines: the simple economics of artificial intelligence*. Harvard Business Press.

Ahmed, A.A.A. and Ganapathy, A., 2021. Creation of automated content with embedded artificial intelligence: a study on learning management system for educational entrepreneurship. *Academy of Entrepreneurship Journal*, *27*(3), pp.1-10.

Ajzen, I., 1991. The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), pp.179-211.

Akter, S., McCarthy, G., Sajib, S., Michael, K., Dwivedi, Y.K., D'Ambra, J. and Shen, K.N., 2021. Algorithmic bias in data-driven innovation in the age of AI. *International Journal of Information Management*, *60*, p.102387.

Alam, A., 2021, November. Possibilities and apprehensions in the landscape of artificial intelligence in education. In *2021 International Conference on Computational Intelligence and Computing Applications (ICCICA)* (pp. 1-8). IEEE.

Alboqami, H., 2023. Trust me, I'm an influencer!-Causal recipes for customer trust in artificial intelligence influencers in the retail industry. *Journal of Retailing and Consumer Services*, *72*, p.103242.

Alkhoori, A., Kuhail, M.A. and Alkhoori, A., 2020, April. UniBud: A virtual academic adviser. In *2020 12th Annual Undergraduate Research Conference on Applied Computing (URC)*, pp. 1-4.

Alqurashi, D.R., Alkhaffaf, M., Daoud, M.K., Al-Gasawneh, J.A. and Alghizzawi, M., 2023. Exploring the impact of artificial intelligence in personalized content marketing: a contemporary digital marketing. *Migration Letters*, *20*(S8), pp.548-560.

Ameen, N., Cheah, J.H. and Kumar, S., 2022. It's all part of the customer journey: The impact of augmented reality, chatbots, and social media on the body image and self-esteem of Generation Z female consumers. *Psychology & Marketing*, *39*(11), pp.2110-2129.

Andrews, T., 2012. What is social constructionism?. *Grounded theory review*, *11*(1).

Anshari, M., Almunawar, M. N., Lim, S. A., Al-Mudimigh, A., 2018. Customer relation- ship management and big data-enabled: Personalization & customization of services. Applied Computing and Informatics, 15 (2), pp. 94–101.

Arasu, B.S., Seelan, B.J.B. and Thamaraiselvan, N., 2020. A machine learning-based approach to enhancing social media marketing. *Computers & Electrical Engineering*, *86*, p.106723.

Arevalillo, J.M., 2019. A machine learning approach to assess price sensitivity with application to automobile loan segmentation. *Applied Soft Computing*, *76*, pp. 390-399.

Arjun, R., Kuanr, A. and Suprabha, K.R., 2021. Developing banking intelligence in emerging markets: Systematic review and agenda. *International Journal of Information Management Data Insights*, *1*(2), p.100026.

Atlas, S., 2023. ChatGPT for higher education and professional development: A guide to conversational AI. Available at: https://digitalcommons.uri.edu/cba_facpubs/548 (Accessed 24 March 2024).

Austin, Z. and Sutton, J., 2014. Qualitative research: Getting started. *The Canadian journal of hospital pharmacy*, *67*(6), p.436.

Aydın, Ö. and Karaarslan, E., 2022. OpenAI ChatGPT generated literature review: Digital twin in healthcare. *Available at SSRN 4308687*.

Azadeh, A. and Zarrin, M., 2016. An intelligent framework for productivity assessment and analysis of human resource from resilience engineering, motivational factors, HSE and ergonomics perspectives. *Safety science*, *89*, pp.55-71.

Bar, A. and Feigenbaum, E.A., 1981. The Handbook of Artificial Intelligence (vol 3). *Stanford University, AQ7*, *305*, p.306.

Barros-Arrieta, D. and García-Cali, E., 2021. Internal branding: conceptualization from a literature review and opportunities for future research. *Journal of Brand Management*, *28*(2), pp.133-151.

Batra, R. and Keller, K.L., 2016. Integrating marketing communications: New findings, new lessons, and new ideas. *Journal of Marketing*, *80*(6), pp.122-145.

Bawack, Ransome Epie, Samuel Fosso Wamba, and Kevin Daniel André Carillo., 2021. "Exploring the role of personality, trust, and privacy in customer experience performance during voice shopping: Evidence from SEM and fuzzy set qualitative comparative analysis." *International Journal of Information Management* 58 (2021). pp. 102309.

Becker, H.S., 1971. *Sociological work*. Transaction publishers.

Becker, R. and Kolster, R., 2012. International student recruitment: Policies and developments in selected countries. *Netherlands Organisation for international cooperation in Higher Education,* pp. 1-104.

Bélanger, F., Crossler, R.E. and Correia, J., 2021. Privacy maintenance in self-digitization: the effect of information disclosure on continuance intentions. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *52*(2), pp.7-24.

Belk, R., 2021. Ethical issues in service robotics and artificial intelligence. The Service Industries Journal, 41(13-14), pp.860-876.

Bell, E., Bryman, A. and Harley, B., 2022. *Business research methods*. Oxford university press.

Benabdelouahed, M.R. and Dakouan, C., 2020. The Use of Artificial Intelligence in Social Media: Opportunities and Perspectives. *Expert Journal of Marketing*, *8*(1), pp. 82-87.

Benaissa, B. and Kobayashi, M., 2023. The consumers' response to product design: a narrative review. *Ergonomics*, *66*(6), pp.791-820.

Benjamin, O.O. and Foye, V.O., 2022. Inclusion, Organizational Resilience, and Sustainable Development in Nigeria: The Role of Digital Innovations. *Environmental Sciences Proceedings*, *15*(1), p.27.

Bennani, S., Maalel, A. and Ben Ghezala, H., 2022. Adaptive gamification in E-learning: A literature review and future challenges. *Computer Applications in Engineering Education*, *30*(2), pp.628-642.

Benrahal, Mohamed, El Mostafa Bourhim, Ali Dahane, Oumayma Labti, and Aziz Akhiate. "UTAUT2 Model to Explain the Adoption of Augmented Reality Technology in Education: An Empirical Study in Morocco." In *Proceedings of the 2nd International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2022, 2*, pp. 491-500.

Berger, P.L. and Luckmann, T., 1967. *The social construction of reality: A treatise in the sociology of knowledge*. Anchor.

Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., & Schweidel, D. A. (2020). Uniting the tribes: Using text for marketing insight. Journal of Marketing, 84(1), pp. 1–25.

Berrios, R., & Lucca, N. (2006). Qualitative methodology in counselling research Recent contributions and challenges for a new century. Journal of Counselling & Development, 84(1), pp. 174-186.

Bhutoria, A., 2022. Personalized education and artificial intelligence in United States, China, and India: A systematic Review using a Human-In-The-Loop model. *Computers and Education: Artificial Intelligence*, 2022, p.100068.

Biesta, G., 2021. PRAGMATISM AND THE PHILOSOPHICAL FOUNDATIONS OF MIXED METHODS RESEARCH[1]. *SAGE handbook of mixed methods in social & behavioral research*, p.95.

Bigne, E., Nicolau, J.L. and William, E., 2021. Advance booking across channels: The effects on dynamic pricing. *Tourism Management*, *86*, pp. 1-12.

Biwer, F. (2021). How Georgia State University used AI to streamline student recruitment. EdTech Magazine [online]. Available at: https://edtechmagazine.com/higher/article/2021/07/how-georgia-state-university-used-ai-streamline-student-recruitment (Accessed 26 February 2023).

Blümel, J.H., Zaki, M. and Bohné, T., 2024. Personal touch in digital customer service: a conceptual framework of relational personalization for conversational AI. *Journal of Service Theory and Practice*, *34*(1), pp.33-65.

Blut, M., Wang, C., Wünderlich, N.V. and Brock, C., 2021. Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, *49*, pp.632-658.

Bock, D.E., Poole, S.M. and Joseph, M., 2014. Does branding impact student recruitment: A critical evaluation. *Journal of Marketing for Higher Education*, *24*(1), pp.11-21.

Bolton, R. N., McColl-Kennedy, J. R., Cheung, L., Gallan, A., Orsingher, C., Witell, L., Zaki, M., 2018. Customer experience challenges: Bringing together digital, physical, and social realms. Journal of Service Management, 29 (5), pp. 776–808.

Bornet, P., Barkin, I. and Wirtz, J., 2021. *Intelligent automation: Welcome to the world of hyperautomation: learn how to harness artificial intelligence to boost business & make our world more human*.

Brandtzaeg, P.B. and Følstad, A., 2018. Chatbots: changing user needs and motivations. *interactions*, *25*(5), pp.38-43.

Braun, V. and Clarke, V., 2006. Using thematic analysis in psychology. *Qualitative research in psychology*, *3*(2), pp.77-101.

Braun, V. and Clarke, V., 2012. *Thematic analysis*. American Psychological Association.

Braun, V. and Clarke, V., 2013. Successful qualitative research: A practical guide for beginners. *Successful qualitative research*, pp.1-400.

Breves, P., 2021. Biased by being there: The persuasive impact of spatial presence on cognitive processing. *Computers in Human Behavior*, *119*, p.106723.

Brill, T.M., Munoz, L. and Miller, R.J., 2022. Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. In *The Role of Smart Technologies in Decision Making* (pp. 35-70). Routledge.

British Educational Research Association, 2018. *Ethical guidelines for educational research*. 4th edn. Available at: https://www.bera.ac.uk/researchers-resources/publications/ethical-guidelines-for-educational-research-2018 (Accessed: 13 May 2024).

Bryman, A., 2003. *Quantity and quality in social research* (Vol. 18). Routledge.

Buchanan, B.G. and Smith, R.G., 1988. Fundamentals of expert systems. *Annual review of computer science*, *3*(1), pp.23-58.

Buldeo Rai, H.B., Verlinde, S. and Macharis, C., 2019. The “next day, free delivery” myth unravelled: Possibilities for sustainable last mile transport in an omnichannel environment. *International Journal of Retail & Distribution Management*, 47(1), pp. 39-54.

Burr, V., 2015. *Social constructionism*. Routledge.

Caballé, S. and Conesa, J., 2019. Conversational agents in support for collaborative learning in MOOCs: An analytical review. In *Advances in Intelligent Networking and Collaborative Systems: The 10th International Conference on Intelligent Networking and Collaborative Systems (INCoS-2018)* (pp. 384-394). Springer International Publishing.

Camilleri, M.A. and Kozak, M., 2022. Utilitarian motivations to engage with travel websites: an interactive technology adoption model. *Journal of Services Marketing*, (ahead-of-print).

Campbell, C., Sands, S., Ferraro, C., Tsao, H.Y.J. and Mavrommatis, A., 2020. From data to action: How marketers can leverage AI. *Business Horizons*, *63*(2), pp.227-243.

Capatina, A., Kachour, M., Lichy, J., Micu, A., Micu, A.E. and Codignola, F., 2020. Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users’ expectations. *Technological Forecasting and Social Change*, *151*, p.119794.

Carrillo, M.R., 2020. Artificial intelligence: From ethics to law. *Telecommunications Policy*, *44*(6), pp. 1-16.

Carter, E. and Knol, C., 2020. Chatbots—an organisation’s friend or foe?. *Research in Hospitality Management*, *9*(2), pp.113-115.

Castillo, E., Gutierrez, J.M. and Hadi, A.S., 2012. *Expert systems and probabilistic network models*. Springer Science & Business Media.

Ceha, J. and Law, E., 2022, April. Expressive Auditory Gestures in a Voice-Based Pedagogical Agent. In *CHI Conference on Human Factors in Computing Systems, 2022,* pp. 1-13.

Chakma, R., Paul, J. and Dhir, S., 2021. Organizational ambidexterity: A review and research agenda. *IEEE Transactions on Engineering Management*, *71*, pp.121-137.

Chan-Olmsted, S., Chen, H. and Kim, H.J., 2024. In smartness we trust: consumer experience, smart device personalization and privacy balance. *Journal of Consumer Marketing*, *41*(6), pp.597-609.

Chandra, S., Verma, S., Lim, W.M., Kumar, S. and Donthu, N., 2022. Personalization in personalized marketing: Trends and ways forward. *Psychology & Marketing*, pp. 1-34.

Charmaz, K., 2021. The genesis, grounds, and growth of constructivist grounded theory. *Developing grounded theory: The second generation revisited*, pp.153-187.

Checkel, J.T., 2004. Social constructivisms in global and European politics: a review essay. *Review of International Studies*, *30*(2), pp.229-244.

Chen, L., Chen, P. and Lin, Z., 2020. Artificial intelligence in education A review. Ieee Access, 8, pp.75264-75278.

Chen, H.L., Vicki Widarso, G. and Sutrisno, H., 2020. A chatbot for learning Chinese. Learning achievement and technology acceptance. Journal of Educational Computing Research, 58(6), pp.1161-1189.

Chen, Y., Jensen, S., Albert, L.J., Gupta, S. and Lee, T., 2023. Artificial intelligence (AI) student assistants in the classroom: Designing chatbots to support student success. *Information Systems Frontiers*, *25*(1), pp.161-182.

Chen, Q., Yin, C. and Gong, Y., 2023. Would an AI chatbot persuade you An empirical answer from the elaboration likelihood model. Information Technology & People. Vol. ahead-of-print No. ahead-of-print.

Cheng, Y. and Jiang, H., 2022. Customer–brand relationship in the era of artificial intelligence understanding the role of chatbot marketing efforts. Journal of Product & Brand Management, 31(2), pp.252-264.

Chi, N.T.K. and Nam, V.H., 2022. The Impact of AI Chatbot on Long-Term Relationships between Customers and Hotels. *VNU University of Economics and Business*, *2*(6), pp. 1-10.

Chintalapati, S. and Pandey, S.K., 2022. Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research*, *64*(1), pp.38-68.

Choung, H., David, P. and Ross, A., 2023. Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human–Computer Interaction*, *39*(9), pp.1727-1739.

Chu, T.H., Chao, C.M., Liu, H.H. and Chen, D.F., 2022. Developing an Extended Theory of UTAUT 2 Model to Explore Factors Influencing Taiwanese Consumer Adoption of Intelligent Elevators. SAGE Open, 12(4), p.2158244022114

Chugh, R. and Ruhi, U., 2018. Social media in higher education: A literature review of Facebook. *Education and Information Technologies*, *23*, pp.605-616.

Cingillioglu, I., Gal, U., & Prokhorov, A. 2021. An analysis of tweet relevance, twitter activity and student preferences for universities. In 2021 19th international conference on information technology based higher education and training (ITHET), pp. 01–10. IEEE.

Cingillioglu, I., Gal, U. and Prokhorov, A., 2023. Social media marketing for student recruitment an algorithmically sequenced literature review. Journal of Marketing for Higher Education, pp.1-23.

Clandinin, D. and Caine, V., 2008. Narrative Inquiry. In Lisa M. Given (Ed.), *The Sage Encyclopedia of Qualitative Research Methods.* pp. 542-545. Thousand Oaks, CA: SAGE Publications, Inc.

Clandinin, D.J. and Connelly, M., 2000. *Narrative inquiry*. Taylor Francis

Clandinin, D.J., 2022. *Engaging in narrative inquiry*. Routledge.

Clark, T., Foster, L., Bryman, A. and Sloan, L., 2021. *Bryman's social research methods*. Oxford university press.

Cloarec, J., 2022. Privacy controls as an information source to reduce data poisoning in artificial intelligence-powered personalization. *Journal of Business Research*, *152*, pp.144-153.

Colicev, A., Malshe, A., Pauwels, K., O'Connor, P., 2018. Improving consumer mindset metrics and shareholder value through social media: The different roles of owned and earned media. *Journal of Marketing*, *82*(1), pp.37-56.

Comendador, B. E. V., Francisco, B. M. B., Medenilla, J. S., Nacion, S. M. T., & Serac, T. B. E. (2015). Pharmabot: A Pediatric Generic Medicine Consultant Chatbot. *Journal of Automation and Control Engineering*, *3*(2), pp. 137–140.

Cope, B., Kalantzis, M. and Searsmith, D., 2021. Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. *Educational Philosophy and Theory*, *53*(12), pp.1229-1245.

Coronado, E., Itadera, S. and Ramirez-Alpizar, I.G., 2023. Integrating Virtual, Mixed, and Augmented Reality to Human–Robot Interaction Applications Using Game Engines: A Brief Review of Accessible Software Tools and Frameworks. *Applied Sciences*, *13*(3), p.1292.

Cox, A.M., 2021. Exploring the impact of Artificial Intelligence and robots on higher education through literature-based design fictions. *International Journal of Educational Technology in Higher Education*, *18*(1), p.3.

Crawford, K., 2021. *The Atlas of AI*. Yale University Press.

Creswell, J.W. and Inquiry, Q., 1998. Research design: Choosing among five traditions.

Creswell, J.W., Plano Clark, V.L., Gutmann, M.L. and Hanson, W.E., 2003. An expanded typology for classifying mixed methods research into designs. *A. Tashakkori y C. Teddlie, Handbook of mixed methods in social and behavioral research*, pp.209-240.

Creswell, J.W., 2014. *Qualitative, quantitative and mixed methods approaches*. Sage.

Creswell, J.W. and Báez, J.C., 2020. *30 essential skills for the qualitative researcher*. Sage Publications.

Creswell, J.W. and Plano Clark, V.L., 2023. Revisiting mixed methods research designs twenty years later. *Handbook of mixed methods research designs*, pp.21-36.

Crowe, D., LaPierre, M. and Kebritchi, M., 2017. Knowledge based artificial augmentation intelligence technology: Next step in academic instructional tools for distance learning. *TechTrends*, *61*(5), pp.494-506.

Cunningham-Nelson, S., Boles, W., Trouton, L. and Margerison, E., 2019. A review of chatbots in education: practical steps forward. In *30th Annual Conference for the Australasian Association for Engineering Education (AAEE 2019): Educators Becoming Agents of Change: Innovate, Integrate, Motivate*, pp. 299-306.

Danielescu, A. and Christian, G., 2018, April. A bot is not a polyglot: Designing personalities for multi-lingual conversational agents. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems*, pp. 1-9.

Das, B., Reza, A.M.M., Mohammad, N. and Razo, S.H., 2020, June. Smart Grid Dynamic Pricing Algorithm for Benefit Maximization of Service Providers and Consumers. In *2020 IEEE Region 10 Symposium (TENSYMP)*, pp. 206-209.

Daugherty, P. R., & Wilson, H. J. (2018). Human + Machine: Reimagining Work in the Age of AI. Harvard Business Press.

Davenport, T.H. and Ronanki, R., 2018. Artificial intelligence for the real world. Harvard business review, 96(1), pp.108-116.

Davenport, T., Guha, A., Grewal, D. and Bressgott, T., 2020. How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, pp.24-42.

Davenport, T.H., Guha, A. and Grewal, D., 2021. How to design an AI marketing strategy. *Harvard Business Review*, *99*(4), pp.42-47.

Davis, F.D., 1987. User acceptance of information systems: the technology acceptance model (TAM).

De Bellis, E. and Johar, G.V., 2020. Autonomous shopping systems: Identifying and overcoming barriers to consumer adoption. *Journal of Retailing*, *96*(1), pp.74-87.

Dekimpe, M.G., 2020. Retailing and retailing research in the age of big data analytics. *International Journal of Research in Marketing*, *37*(1), pp.3-14.

Deloitte, 2019. *Conversational AI: The next wave of customer and employee experiences*. Deloitte Touche Tohmatsu Limited. Available at: https://www2.deloitte.com/content/dam/Deloitte/au/Documents/strategy/au-deloitte-conversational-ai.pdf [Accessed 23 May 2022].

Dell'Aquila, E., Vallone, F., Zurlo, M.C., Marocco, D., 2022. SG-ACCORD: Designing Virtual Agents for Soft Skills Training in the School Context. *Education Sciences*, *12*(3), p.174.

Demmers, J., Weltevreden, J.W. and van Dolen, W.M., 2020. Consumer engagement with brand posts on social media in consecutive stages of the customer journey. *International Journal of Electronic Commerce*, *24*(1), pp.53-77.

Deng, J. and Lin, Y., 2022. The benefits and challenges of ChatGPT: An overview. *Frontiers in Computing and Intelligent Systems*, *2*(2), pp.81-83.

Denzin, N.K. and Lincoln, Y.S. eds., 2011. *The Sage handbook of qualitative research*. sage.

Deriu, J., Rodrigo, A., Otegi, A., Echegoyen, G., Rosset, S., Agirre, E. and Cieliebak, M., 2021. Survey on evaluation methods for dialogue systems. *Artificial Intelligence Review*, *54*, pp.755-810.

Devoe, M., 1956. Effective Advertising Copy.

Dewey, J., 1938. Experience and education. New York: Collier Books.

De Wit, H. and Altbach, P.G., 2021. Internationalization in higher education global trends and recommendations for its future. *Policy Reviews in Higher Education*, 5(1), pp.28-46.

Dhawan, S. and Batra, G., 2020. Artificial Intelligence in Higher Education: Promises, Perils, and Perspective. *Expanding Knowledge Horizon. OJAS*, *11*, pp.11-22.

Diederich, S., Brendel, A.B., Kolbe, L.M., 2019. Towards a taxonomy of platforms for conversational agent design.

Dimitriadis, G., 2020. Evolution in education: chatbots. *Homo Virtualis*, *3*(1), pp.47-54.

Divekar, R.R., Lepp, H., Chopade, P., Albin, A., Brenner, D. and Ramanarayanan, V., 2021, July. Conversational Agents in Language Education: Where They Fit and Their Research Challenges. In *International Conference on Human-Computer Interaction, 2021,* pp. 272-279.

Dreyfus, H.L., 1972. *What Computers Can't Do: A critique of artificial intelligence*. Harper & Row.

Duan, N., Bhaumik, D.K., Palinkas, L.A. and Hoagwood, K., 2015. Optimal design and purposeful sampling: Complementary methodologies for implementation research. *Administration and Policy in Mental Health and Mental Health Services Research*, *42*, pp.524-532.

Duan, Y., Edwards, J.S. and Dwivedi, Y.K., 2019. Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International journal of information management*, *48*, pp.63-71.

Duncan, T. and Moriarty, S., 1997. The IM audit: Testing the fabric of integration. *Integrated Marketing Communications Research Journal*, *3*(1), pp.3-10.

Dwivedi, Y.K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A. and Galanos, V., 2021. Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*, pp.1 - 47.

Dwivedi, Y.K. and Wang, Y., 2022. Guest editorial: Artificial intelligence for B2B marketing: Challenges and opportunities. *Industrial Marketing Management*, *105*, pp.109-113.

Dwivedi, Yogesh K., Nir Kshetri, Laurie Hughes, Emma Louise Slade, Anand Jeyaraj, Arpan Kumar Kar, Abdullah M. Baabdullah et al., 2023. "“So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy." *International Journal of Information Management* 71 (2023): 102642.

Eagle, L., Czarnecka, B., Dahl, S. and Lloyd, J., 2020. *Marketing communications*. Routledge.

Egan, J., 2015. Marketing communications. Sage.

Elnozahy, W.A., El Khayat, G.A., Cheniti-Belcadhi, L. and Said, B., 2019. Question Answering System to Support University Students’ Orientation, Recruitment and Retention. *Procedia Computer Science*, *164*, pp.56-63.

Erasmus, A.C., Boshoff, E. and Rousseau, G.G., 2001. Consumer decision-making models within the discipline of consumer science: a critical approach. *Journal of Consumer Sciences*, *29*, pp. 82-90.

Eriksson, T., Bigi, A., & Bonera, M. 2020. Think with me, or think for me On the future role of artificial intelligence in marketing strategy formulation. The TQM Journal, 32(4), pp. 795-814.

Ericsson, A., and Simon, H. "Verbal reports on thinking." (2003). MIT Press

Ernst & Young Report, 2016. From Innovation to Expectation – How M & E Leaders are Responding to Gen Z. Retrie from http://www.ey.com/Publication/vwLUAssets/ey-media-entertainment-leaders-respond-to-gen-z/$FILE/ey-media-entertainment-leaders-respond-to-gen-z.pdf

European Parliament, 203. EU AI Act: first regulation on Artificial Intelligence [online]. Available at: https://www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence (Accessed 12 March 2023).

European Parliament, 2023a. What is artificial intelligence and how is it used? [online]. Available at: https://www.europarl.europa.eu/topics/en/article/20200827STO85804/what-is-artificial-intelligence-and-how-is-it-used (Accessed 12 March 2023).

Fan, H., Gao, W. and Han, B., 2023. Are AI chatbots a cure-all? The relative effectiveness of chatbot ambidexterity in crafting hedonic and cognitive smart experiences. *Journal of Business Research*, *156*, p.113526.

Feine, J., Gnewuch, U., Morana, S. and Maedche, A., 2019. A taxonomy of social cues for conversational agents. *International Journal of Human-Computer Studies*, *132*, pp.138-161.

Ferrell, O.C. and Ferrell, L., 2020. Technology challenges and opportunities facing marketing education. *Marketing Education Review*, *30*(1), pp.3-14.

Fitzpatrick, K.K., Darcy, A. and Vierhile, M., 2017. Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): a randomized controlled trial. *JMIR mental health*, *4*(2), p.e7785.

Flechsig, C., Anslinger, F. and Lasch, R., 2022. Robotic Process Automation in purchasing and supply management: A multiple case study on potentials, barriers, and implementation. *Journal of Purchasing and Supply Management*, *28*(1), p.100718.

Forlizzi, J. and Battarbee, K., 2004, August. Understanding experience in interactive systems. In *Proceedings of the 5th conference on Designing interactive systems: processes, practices, methods, and techniques* (pp. 261-268).

Fortuna, P. and Gorbaniuk, O., 2022. What Is Behind the Buzzword for Experts and Laymen: Representation of "Artificial Intelligence" in the IT-Professionals' and Non-Professionals' Minds. *Europe's Journal of Psychology*, *18*(2), pp.207-218.

Følstad, A. and Brandtzæg, P.B., 2017. Chatbots and the new world of HCI. *interactions*, *24*(4), pp.38-42.

Følstad, A., Skjuve, M. and Brandtzaeg, P.B., 2018, October. Different chatbots for different purposes: towards a typology of chatbots to understand interaction design. In *International Conference on Internet Science* (pp. 145-156). Springer, Cham.

Følstad, A. and Kvale, K., 2018. Customer journeys: a systematic literature review. *Journal of Service Theory and Practice*.

Følstad, A. and Brandtzaeg, P.B., 2020. Users' experiences with chatbots findings from a questionnaire study. Quality and User Experience, 5(1), pp. 1-14.

Følstad, A., Araujo, T., Law, E.L.C., Brandtzaeg, P.B., Papadopoulos, S., Reis, L., Baez, M., Laban, G., McAllister, P., Ischen, C. and Wald, R., 2021. Future directions for chatbot research: an interdisciplinary research agenda. *Computing*, *103*(12), pp.2915-2942.

Fritze, M.P., Völckner, F. and Melnyk, V., 2024. Behavioral Labeling: Prompting Consumer Behavior Through Activity Tags. *Journal of Marketing*, 88(4), pp.22-39.

Frølich, N. and Stensaker, B., 2010. Student recruitment strategies in higher education: promoting excellence and diversity?. *International Journal of Educational Management*, *24*(4), pp.359-370.

Fry, H., 2019. Hello World: How to Be Human in the Age of the Machine, Transworld Publishers, London

Gabrielova, K. and Buchko, A.A., 2021. Here comes Generation Z: Millennials as managers. *Business Horizons*, *64*(4), pp.489-499.

Gansser, O.A. and Reich, C.S., 2021. A new acceptance model for artificial intelligence with extensions to UTAUT2. An empirical study in three segments of application. Technology in Society, 65, p.101535.

Gao, J., Galley, M. and Li, L., 2019. Neural approaches to conversational AI. *Foundations and trends® in information retrieval*, *13*(2-3), pp.127-298.

Gao, Y. and Liu, H., 2022. Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. *Journal of Research in Interactive Marketing*, (ahead-of-print), pp.1-18.

García de Blanes Sebastián, M., Sarmiento Guede, J.R. and Antonovica, A., 2022. Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*, p.993935.

Gardiner, A. and Smith, M.A., 2021. Conversational AI as an Emerging Technology. In *Proceedings of the EDSIG Conference ISSN*, 2473, p. 4901.

Geertz, C., 1987. " From the native's point of view": On the nature of anthropological understanding. *Bulletin of the american academy of arts and sciences*, pp.26-45.

Gerdes, D.A. and Conn, J.H., 2001. A user-friendly look at qualitative research methods. *Physical Educator*, *58*(4), p.183.

Garske, B., Bau, A. and Ekardt, F., 2021. Digitalization and AI in European Agriculture: A Strategy for Achieving Climate and Biodiversity Targets?. *Sustainability*, *13*(9), p.4652.

George, A.S. and George, A.H., 2023. A Review of ChatGPT AI's Impact on Several Business Sectors. *Partners Universal International Innovation Journal*, *1*(1), pp.9-23.

Gerlich, M., Elsayed, W. and Sokolovskiy, K., 2023. Artificial intelligence as toolset for analysis of public opinion and social interaction in marketing: identification of micro and nano influencers. *Frontiers in Communication*, *8*, p.1075654.

Ghazali, E., Mutum, D.S. and Lun, N.K., 2023. Expectations and beyond: The nexus of AI instrumentality and brand credibility in voice assistant retention using extended expectation-confirmation model. *Journal of Consumer Behaviour*, 2023, p. 1-21

Gill, K.S., 2016. Artificial super intelligence: beyond rhetoric. *Ai & Society*, *31*(2), pp.137-143.

Glaser, B. and Strauss, A., 1967. *The Discovery of Grounded Theory: Strategies for qualitative research*. New York: Aldine De Gruyter.

Glaser, B.G., 2002. Conceptualization: On theory and theorizing using grounded theory. *International Journal of Qualitative Methods*, *1*(2), pp.23-38.

Glyptou, K., 2021. Destination image co-creation in times of sustained crisis. *Tourism Planning & Development*, *18*(2), pp.166-188.

Gnewuch, U., Morana, S. and Maedche, A., 2017, December. Towards Designing Cooperative and Social Conversational Agents for Customer Service. In *ICIS*, 38, pp. 1- 13.

Gonçalves, G.S., Ribeiro, T.D.L.S.A., Teixeira, J.E.V. and Costa, B.K., 2022. The deployment of chatbot to improve customer service in higher education institutions during COVID-19. *International Journal of Innovation*, *10*(1), pp.178-203.

Goodwin, N.C., 1987. Functionality and usability. *Communications of the ACM*, *30*(3), pp.229-233.

Gray, K. 2017. AI can be a troublesome teammate. [online]. Harvard Business Review. Available at: https://hbr.org/2017/07/ai-can-be-a-troublesome-teammate (Accessed 15 February 2024).

Gray, C.C., Perkins, D. and Ritsos, P.D., 2020. Degree pictures: Visualizing the university student journey. *Assessment & Evaluation in Higher Education*, *45*(4), pp.568-578.

Green, B. and Viljoen, S., 2020, January. Algorithmic realism: expanding the boundaries of algorithmic thought. In *Proceedings of the 2020 conference on fairness, accountability, and transparency* (pp. 19-31).

Grewal, D., Herhausen, D., Ludwig, S. and Ordenes, F.V., 2022. The future of digital communication research: Considering dynamics and multimodality. *Journal of Retailing*, *98*(2), pp.224-240.

Guba, E.G. and Lincoln, Y.S., 1994. Competing paradigms in qualitative research. *Handbook of qualitative research*, *2*(163-194), p.105.

Guillemin, M. and Gillam, L., 2004. Ethics, reflexivity, and “ethically important moments” in research. Qualitative inquiry, 10(2), pp.261-280.

Gummesson, E., 1991. Service quality: a holistic view. *Service quality: Multidisciplinary and multinational perspectives*, pp.3-22.

Guo, J., Zhang, W., Fan, W. and Li, W., 2018. Combining geographical and social influences with deep learning for personalized point-of-interest recommendation. *Journal of Management Information Systems*, *35*(4), pp.1121-1153.

Gursoy, D., Li, Y. and Song, H., 2023. ChatGPT and the hospitality and tourism industry: an overview of current trends and future research directions. *Journal of Hospitality Marketing & Management*, *32*(5), pp.579-592.

Gutierrez, A., O'Leary, S., Rana, N.P., Dwivedi, Y.K. and Calle, T., 2019. Using privacy calculus theory to explore entrepreneurial directions in mobile location-based advertising: Identifying intrusiveness as the critical risk factor. *Computers in Human Behavior*, *95*, pp.295-306.

Guzzini, S., 2005. The Concept of Power A Constructivist Analysis. Millennium Journal of International Studies 33(3). pp.495–521.

Hacking, I., (1995). The Looping Effects of Human Kinds. In Causal Cognition: A Multi-Disciplinary Approach, edited by Dan Sperber, David Premack, and Ann J. Premack. Oxford: Clarendon Press.

Haenlein, M. and Kaplan A., 2019. A Brief History of AI: On the Past, Present, and Future of Artificial Intelligence. *California Management Review*, 61(4), pp. 5–14.

Haleem, A., Javaid, M., Singh, R.P. and Suman, R., 2022. Medical 4.0 technologies for healthcare: Features, capabilities, and applications. *Internet of Things and Cyber-Physical Systems*, 2, pp. 12-30.

Haleem, A., Javaid, M., Qadri, M.A., Singh, R.P. and Suman, R., 2022. Artificial intelligence (AI) applications for marketing: A literature-based study. *International Journal of Intelligent Networks*.

Hall, S.R., 1915. *Writing an Advertisement: A Analysis of the Methods and the Mental Processes that Play a Part in the Writing of Successful Advertising*. Houghton Mifflin.

Hammersley, M. and Atkinson, P., 2019. *Ethnography: Principles in practice*. Routledge.

Haque, M.U., Dharmadasa, I., Sworna, Z.T., Rajapakse, R.N. and Ahmad, H., 2022. " I think this is the most disruptive technology": Exploring Sentiments of ChatGPT Early Adopters using Twitter Data. *arXiv preprint arXiv:2212.05856*.

Hartmann, J., Huppertz, J., Schamp, C., & Heitmann, M., 2019. Comparing automated text classification methods. *International Journal of Research in Marketing*, 36(1), pp. 20–38.

Hari, H., Iyer, R. and Sampat, B., 2021. Customer brand engagement through chatbots on bank websites–examining the antecedents and consequences. *International Journal of Human–Computer Interaction*, pp.1-16.

Hassenzahl, M., 2018. The thing and I: understanding the relationship between user and product. *Funology 2: from usability to enjoyment*, pp.301-313.

Helal, G., Ozuem, W. and Lancaster, G., 2018. Social media brand perceptions of millennials. *International Journal of Retail & Distribution Management*, *46*(10), pp.977-998.

Hill, J., Ford, W.R. and Farreras, I.G., 2015. Real conversations with artificial intelligence: A comparison between human–human online conversations and human–chatbot conversations. *Computers in human behavior*, *49*, pp.245-250.

Ho, R.C., 2021. Chatbot for online customer service: Customer engagement in the era of artificial intelligence. In *Impact of globalization and advanced technologies on online business models* (pp. 16-31). IGI Global.

Hollebeek, L.D., Menidjel, C., Sarstedt, M., Jansson, J. and Urbonavicius, S., 2024. Engaging consumers through artificially intelligent technologies: Systematic review, conceptual model, and further research. *Psychology & Marketing*, 41 (4), pp.1-19.

Holstein, J.A. and Gubrium, J.F. eds., 2013. *Handbook of constructionist research*. Guilford Publications.

Holzinger, A., Langs, G., Denk, H., Zatloukal, K. and Müller, H., 2019. Causability and explainability of artificial intelligence in medicine. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *9*(4), pp. 1312.

Hong, S.R., Hullman, J. and Bertini, E., 2020. Human factors in model interpretability: Industry practices, challenges, and needs. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW1), pp.1-26.

Horowitz, M.C., Kahn, L. and Samotin, L.R., 2022. A Force for the Future: A High-Reward, Low-Risk Approach to AI Military Innovation. *Foreign Affairs*, *101*, p.157.

Hovy, D., Melumad, S., Inman, J. J., 2021. Wordify: A tool for discovering and differentiating consumer vocabularies. Journal of Consumer Research, 48(3), pp. 394–414.

Hoyer, W.D., Kroschke, M., Schmitt, B., Kraume, K. and Shankar, V., 2020. Transforming the customer experience through new technologies. *Journal of Interactive Marketing*, *51*, pp.57-71.

Hu, P., Gong, Y., Lu, Y. and Ding, A.W., 2023. Speaking vs. listening? Balance conversation attributes of voice assistants for better voice marketing. *International Journal of Research in Marketing*, *40*(1), pp.109-127.

Huang, C.Y. and Yang, M.C., 2020. Empirical investigation of factors influencing consumer intention to use an artificial intelligence-powered mobile application for weight loss and health management. *Telemedicine and e-Health*, *26*(10), pp.1240-1251.

Huang, M.H. and Rust, R.T. 2018. Artificial Intelligence in Service, Journal of Service Research, 21(2), pp. 155–172.

Huang, M.H. and Rust, R.T., 2021. A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science, 49(1), pp.30-50.

Huang, M.H. and Rust, R.T., 2022. A framework for collaborative artificial intelligence in marketing. *Journal of Retailing*, *98*(2), pp.209-223.

Humphrey, O. and Lowe, T., 2017. Exploring how a ‘Sense of Belonging’ is facilitated at different stages of the student journey in Higher Education. *The Journal of Educational Innovation, Partnership and Change*, *3*(1), pp.172-188.

Hwang, G.J. and Chang, C.Y., 2021. A review of opportunities and challenges of chatbots in education. *Interactive Learning Environments*, pp.1-14.

Jackson, A.Y. and Mazzei, L.A., 2022. *Thinking with theory in qualitative research*. Taylor & Francis.

Jain, M., Kumar, P., Kota, R. and Patel, S.N., 2018, June. Evaluating and informing the design of chatbots. In *Proceedings of the 2018 designing interactive systems conference*, pp. 895-906.

Janssen, A., Passlick, J., Rodríguez Cardona, D. and Breitner, M. H., 2020. Virtual assistance in any context. *Business & Information Systems Engineering*, *62*(3), pp. 211–225.

Janssen, A., Rodríguez Cardona, D. and Breitner, M. H**.,** 2020**.** More than FAQ! Chatbot taxonomy for business-to-business customer services. In Følstad, A. et al. (Eds.). Chatbot Research and Design (CONVERSATIONS 2020), *Lecture Notes in Computer Science, 12604*, pp. 175–189.

Jarek, K. and Mazurek, G., 2019. Marketing and Artificial Intelligence. *Central European Business Review*, *8*(2), pp. 46-55.

Jeckells, H., 2022. An investigation into the influential factors that impact consumer decision-making among prospective online MBA students. *Journal of Marketing for Higher Education*, 32(2), pp.278-304.

John, S.P., Walford, R. and Purayidathil, J., 2022. Factors affecting the adoption of social media in marketing of higher education An empirical analysis. FIIB Business Review, 11(4), pp.422-437.

Johnson, J., 2021. The end of military-techno Pax Americana? Washington's strategic responses to Chinese AI-enabled military technology. *The Pacific Review*, *34*(3), pp. 351-378.

Johnson, J.L., Adkins, D. and Chauvin, S., 2020. Qualitative research in pharmacy education: A review of the quality indicators of rigor in qualitative research. *American Journal of Pharmaceutical Education*, *84*(1), pp.138-146.

Jones, C.L.E., Hancock, T., Kazandjian, B. and Voorhees, C.M., 2022. Engaging the Avatar: The effects of authenticity signals during chat-based service recoveries. *Journal of Business Research*, *144*, pp.703-716.

Ji, H., Han, I. and Ko, Y., 2023. A systematic review of conversational AI in language education: Focusing on the collaboration with human teachers. *Journal of Research on Technology in Education*, *55*(1), pp.48-63.

Jiang, K., Qin, M. and Li, S., 2022. Chatbots in retail: How do they affect the continued use and purchase intentions of Chinese consumers?. *Journal of Consumer Behaviour*, *21*(4), pp. 756-772.

IBM, 2020. Conversational AI. [online]. Available at: https://www.ibm.com/cloud/learn/conversational-ai. (Accessed 02 January 2023).

Ibrahim, H., Liu, F., Asim, R., Battu, B., Benabderrahmane, S., Alhafni, B., Adnan, W., Alhanai, T., AlShebli, B., Baghdadi, R. and Bélanger, J.J., 2023. Perception, performance, and detectability of conversational artificial intelligence across 32 university courses. *Scientific Reports*, *13*(1), p.12187.

Israfilzade, K., 2023. The Role of Generative AI and Anthropomorphism in Shaping Conversational Marketing: Creating a Matrix for Future Research. *The Eurasia Proceedings of Educational and Social Sciences*, *32*, pp.132-142.

Israfilzade, K. and Sadili, N., 2024. Beyond interaction: Generative AI in conversational marketing-foundations, developments, and future directions. *JOURNAL OF LIFE ECONOMICS*, *11*(1), pp.13-29.

Ivanov, S.H. and Umbrello, S., 2021. The ethics of artificial intelligence and robotisation in tourism and hospitality–a conceptual framework and research agenda. *Journal of Smart Tourism*, *1*(4), pp.9-18.

Kania, E.B., 2019. Chinese Military Innovation in the AI Revolution. *The RUSI Journal*, *164*(5-6), pp. 26-34.

Kang, D.S., 2016. Turning inside out: perceived internal branding in customer-firm relationship building. *Journal of Services Marketing*, *30*(4), pp. 462–475.

Kaplan, A. and Haenlein M., 2019. Siri, Siri in My Hand, Who Is the Fairest in the Land? On the Interpretations, Illustrations and Implications of Artificial Intelligence*, Business Horizons*, 62(1), pp. 15–25.

Kaplan, A., 2022. Artificial Intelligence, Business and Civilization. Routledge

Kar, A.K. and Kushwaha, A.K., 2021. Facilitators and barriers of artificial intelligence adoption in business–insights from opinions using big data analytics. *Information Systems Frontiers*, pp.1-24.

Karumathil, A. and Tripathi, R., 2022. Combating Survey Bots: An Integrative Literature Review of Insights and Strategies. In *Academy of Management Proceedings*, 1, p. 10900). Briarcliff Manor, NY 10510: Academy of Management.

Kasinidou, M., Kleanthous, S., Barlas, P. and Otterbacher, J., 2021, March. I agree with the decision, but they didn't deserve this: Future Developers' Perception of Fairness in Algorithmic Decisions. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, pp. 690-700.

Keegan, B.J., Dennehy, D. and Naudé, P., 2022. Implementing Artificial Intelligence in Traditional B2B Marketing Practices: An Activity Theory Perspective. *Information Systems Frontiers*, 2022, pp.1-15.

Khalil, M. and Er, E., 2023. Will ChatGPT get you caught? Rethinking of Plagiarism Detection. *arXiv preprint arXiv:2302.04335*.

Khosrawi-Rad, B., Rinn, H., Schlimbach, R, Gebbing, P., Yang, X., Lattemann, C., Markgraf, D., Robra-Bissantz, S., 2022. "Conversational Agents in Education – A Systematic Literature Review". ECIS 2022 Research Papers. 18.

Kitchen, P.J., Brignell, J., Li, T. and Jones, G.S., 2004. The emergence of IMC: a theoretical perspective. *Journal of advertising research*, *44*(1), pp.19-30.

Klayklung, P., Chocksathaporn, P., Limna, P., Kraiwanit, T. and Jangjarat, K., 2023. Revolutionizing Education with ChatGPT: Enhancing Learning Through Conversational AI. *Universal Journal of Educational Research*, *2*(3), pp.217-225.

Kliatchko, J., 2008. Revisiting the IMC construct: A revised definition and four pillars. *International Journal of Advertising*, *27*(1), pp.133-160.

Killick, D., 2004. Social constructionist approaches to the study of technology. *World Archaeology*, *36*(4), pp.571-578.

Kim, Y., Baylor, A.L. and Shen, E., 2007. Pedagogical agents as learning companions: the impact of agent emotion and gender. *Joukillik*
rnal of Computer Assisted Learning, *23*(3), pp.220-234.

Kim, N.Y., Cha, Y. and Kim, H.S., 2019. Future English learning: Chatbots and artificial intelligence. *Multimedia-Assisted Language Learning*, *22*(3), pp.32-53.

Kim, H., Jiang, J. and Bruce, N.I., 2021. Discovering heterogeneous consumer journeys in online platforms: implications for networking investment. *Journal of the Academy of Marketing Science*, *49*(2), pp.374-396.

Kitchen, P., Kerr, G., E. Schultz, D., McColl, R. and Pals, H., 2014. The elaboration likelihood model: review, critique and research agenda. *European Journal of marketing*, *48*(11/12), pp.2033-2050.

Klaus, P. and Zaichkowsky, J., 2020. AI voice bots: a services marketing research agenda. *Journal of Services Marketing*, *34*(3), pp.389-398.

Klein, K. and Martinez, L.F., 2022. The impact of anthropomorphism on customer satisfaction in chatbot commerce: an experimental study in the food sector. *Electronic Commerce Research*, 2022, pp.1-37.

Knijnenburg, B.P. and Willemsen, M.C., 2016. Inferring Capabilities of Intelligent Agents from Their External Traits. ACM Trans. Interact. Intell. Syst. 6, pp. 1–25.

Knickrehm, C., Voss, M. and Barton, M.C., 2023. Can you trust me? Using AI to review more than three decades of AI trust literature. ECIS 2023 Research Papers. 302

Kokshagina, O. and Schneider, S., 2022. The Digital Workplace: Navigating in a Jungle of Paradoxical Tensions. *California Management Review*, p.1 - 27.

Kühl, N., Mühlthaler, M. and Goutier, M., 2020. Supporting customer-oriented marketing with artificial intelligence: automatically quantifying customer needs from social media. *Electronic Markets*, *30*(2), pp.351-367.

Kuhn, T.S., 1970. The structure of scientific revolutions. enlarged. Chicago Press

Kumar, V., Rajan, B., Venkatesan, R. and Lecinski, J., 2019. Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, *61*(4), pp.135-155.

Labrecque, L.I., Peña, P.Y., Leonard, H. and Leger, R., 2024. Not all sunshine and rainbows: exploring the dark side of AI in interactive marketing. *Journal of Research in Interactive Marketing*, 18 (5), pp.970-999.

Lajante, M., Tojib, D. and Ho, T.I., 2023. When interacting with a service robot is (not) satisfying: The role of customers' need for social sharing of emotion. *Computers in Human Behavior*, *146*, p.107792.

Laranjo, L., Dunn, A.G., Tong, H.L., Kocaballi, A.B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A.Y. and Coiera, E., 2018. Conversational agents in healthcare: a systematic review. *Journal of the American Medical Informatics Association*, *25*(9), pp.1248-1258.

Latour, B. and Woolgar, S., 1979. The social construction of scientific facts. Introduction par Jonas Salk.

Lavidge,R.J. and Steiner, G.A., 1961. "A Model for Predictive Measures of Advertising Effectiveness," Journal of Marketing, pp 59-62.

Le, T. D., Dobele, A. R., & Robinson, L. J. (2019). Information sought by prospective students from social media electronic word-of-mouth during the university choice process. *Journal of Higher Education Policy and Management,* 41(1), pp. 18–34.

Lee, C.J.G., 2012. Reconsidering constructivism in qualitative research. Educational Philosophy and theory, 44(4), pp.403-412.

Lee, M.K., 2018. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society*, *5*(1), p.1-18.

Lee, S.B., 2020. Chatbots and Communication: The Growing Role of Artificial Intelligence in Addressing and Shaping Customer Needs. Business Communication Research and Practice, 3(2), pp.103-111.

Lee, S.M. and Lee, D., 2020. "Untact": a new customer service strategy in the digital age. *Service Business*, *14*(1), pp.1-22.

Lee, H., and Yi, Y., 2022. The impact of self-service versus interpersonal contact on customer–brand relationship in the time of frontline technology infusion. Psychology & Marketing, 39(5), pp. 906–920.
Lemon, K.N. and Verhoef, P.C., 2016. Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), pp.69-96.

Leong, L.Y., Hew, T.S., Ooi, K.B. and Lin, B., 2019. Do electronic word-of-mouth and elaboration likelihood model influence hotel booking. Journal of Computer Information Systems, 59(2), pp.146-160.

Lester, J., Branting, K. and Mott, B., 2004. Conversational agents. The practical handbook of internet computing, pp.220-240.

Lewis, E., 1903. Advertising department: catch-line and argument. The Book-Keeper 15, pp. 124–128.

Li, L., Lassiter, T., Oh, J. and Lee, M.K., 2021, July. Algorithmic hiring in practice: Recruiter and HR Professional's perspectives on AI use in hiring. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 166-176.

Li, C., Xing, W. and Leite, W., 2022. Building socially responsible conversational agents using big data to support online learning: A case with Algebra Nation. *British Journal of Educational Technology*, 53, pp. 776-803.

Libai, B., Bart, Y., Gensler, S., Hofacker, C.F., Kaplan, A., Kötterheinrich, K. and Kroll, E.B., 2020. Brave new world? On AI and the management of customer relationships. *Journal of Interactive Marketing*, *51*, pp.44-56.

Lim, W.M., Kumar, S., Verma, S. and Chaturvedi, R., 2022. Alexa, what do we know about conversational commerce? Insights from a systematic literature review. *Psychology & Marketing*, *39*(6), pp.1129-1155.

Limayem, M., Hirt, S.G. and Cheung, C.M., 2007. How habit limits the predictive power of intention: The case of information systems continuance. *MIS quarterly*, pp.705-737.

Ling, E.C., Tussyadiah, I., Tuomi, A., Stienmetz, J. and Ioannou, A., 2021. Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, *38*(7), pp.1031-1051.

Littman, M., Ajunwa, I., Berger, G., Boutilier, C., Currie, M., Doshi-Velez, F., Hadfield, G., Horowitz, M., Isbell, C., Kitano, H., Levy, K., Lyons, T., Mitchell, M., Shah, J., Sloman, S., Vallor, S., Walsh, T., 2021. Gathering Strength, Gathering Storms: The One Hundred Year Study on Artificial Intelligence (AI100) 2021 Study Panel Report. Stanford University, Stanford, CA

Liu, S. (2021), "Virtual assistant technology – statistics and facts" [online]. Available at: https://www.statista.com/topics/5572/virtual-assistants/ (Accessed on 05 March 2023)

Liu, G., Lei, S.S.I. and Law, R., 2022. Enhancing social media branded content effectiveness: strategies via telepresence and social presence. *Information Technology & Tourism*, 2022, pp.1-19.

Longoni, C., Bonezzi, A. and Morewedge, C.K., 2019. Resistance to medical artificial intelligence. *Journal of Consumer Research*, *46*(4), pp.629-650.

Lomer, S., Papatsiba, V. and Naidoo, R., 2018. Constructing a national higher education brand for the UK: Positional competition and promised capitals. *Studies in Higher Education*, *43*(1), pp.134-153.

Lund, B.D. and Wang, T., 2023. Chatting about ChatGPT: how may AI and GPT impact academia and libraries?. *Library Hi Tech News*.

Lynch, M., 2016. Social constructivism in science and technology studies. Human Studies, 39, pp.101-112.

Ma, L. and Sun, B., 2020. Machine learning and AI in marketing–Connecting computing power to human insights. *International Journal of Research in Marketing*, *37*(3), pp.481-504.

Maarek, Y., 2018, October. Alexa and her shopping journey. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management,* pp. 1-1.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S. and Söllner, M., 2019. AI-based digital assistants. *Business & Information Systems Engineering*, *61*(4), pp.535-544.

Malik, P., Pathania, M. and Rathaur, V.K., 2019. Overview of artificial intelligence in medicine. *Journal of Family Medicine and Primary Care*, *8*(7), pp.2328-2331.

Malik, A., De Silva, M.T., Budhwar, P. and Srikanth, N.R., 2021. Elevating talents' experience through innovative artificial intelligence-mediated knowledge sharing: Evidence from an IT-multinational enterprise. *Journal of International Management*, *27*(4), pp. 1-18.

Malone, T.W., 2018. How human-computer 'Superminds' are redefining the future of work. *MIT Sloan management review*, *59*(4), pp.34-41.

Manthiou, A. and Klaus, P., 2022. The interplaying factors of the robotic tourism experience: The customer journey's touchpoints, context, and qualities. *Technological Forecasting and Social Change*, *177*, pp. 1-9.

Marshall, M.N., 1996. Sampling for qualitative research. *Family practice*, *13*(6), pp.522-526.

Martin, K.D. and Murphy, P.E., 2017. The role of data privacy in marketing. *Journal of the Academy of Marketing Science*, *45*, pp.135-155.

Martos, V., Ahmad, A., Cartujo, P. and Ordoñez, J., 2021. Ensuring agricultural sustainability through remote sensing in the era of agriculture 5.0. *Applied Sciences*, *11*(13), p.5911.

Maxwell, J.A., 2013. *Qualitative research design: An interactive approach*. 3rd ed. Sage publications.

McCullogh, W. S. and Pitts, W., 1943. A logical calculus of the ideas immanent in nervous Activity. *Bulletin of Mathematical Biophysics,* 5, pp. 115-137.

McCarthy, R.V., McCarthy, M.M., Ceccucci, W. and Halawi, L., 2022. *Applying predictive analytics,* Springer International Publishing, pp. 89-121.

McCarthy, J., Minsky, M. L., Rochester, N., Shannon, C. E., 1955. A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence. Available at www-formal.stanford.edu/jmc/history/dartmouth/dartmouth.html (Accessed 02 January 2023).

McCaslin, M.L. and Scott, K.W., 2003. The five-question method for framing a qualitative research study. The qualitative report, 8(3), pp.447-461.

McGuire, W.J., 1978. An Information Processing Model of Advertising Effectiveness. Behavioral and Management Science in Marketing, eds. Harry L. Davis and Alvin H. Silk.

McKinion, J.M. and Lemmon, H.E., 1985. Expert systems for agriculture. *Computers and Electronics in Agriculture*, *1*(1), pp.31-40.

McCloskey, D. and Bennett, G., 2020. Examining artificial intelligence acceptance Exploring smart speaker adoption with the agiunified theory of acceptance and use of technology (UTAUT2). Pennsylvania Economic Review, 27(2), pp. 44-70.

McStay, A., 2022. Replika in the Metaverse: the moral problem with empathy in 'It from Bit'. *AI and Ethics*, pp.1-13.

McTear, M., Callejas, Z., and Griol, D. 2016. *The Conversational Interface: Talking to Smart Devices*, Springer.

McTear, M. and Ashurkina, M., 2024. *Transforming Conversational AI: Exploring the Power of Large Language Models in Interactive Conversational Agents*. Apress.

Mehta, P., Jebarajakirthy, C., Maseeh, H.I., Anubha, A., Saha, R. and Dhanda, K., 2022. Artificial intelligence in marketing: A meta-analytic review. *Psychology & Marketing*, *39*(11), pp.2013-2038.

Miao, F., Kozlenkova, I.V., Wang, H., Xie, T. and Palmatier, R.W., 2022. An emerging theory of avatar marketing. *Journal of Marketing*, *86*(1), pp.67-90.

Michels, L., Ochmann, J., Tiefenbeck, V. and Laumer, S., 2022. The acceptance of AI-based recommendations: an elaboration likelihood perspective. Wirtschaftsinformatik 2022 Proceedings. 1.

Miles, M.B. and Huberman, A.M., 1994. *Qualitative data analysis: An expanded sourcebook*. Sage.

Miner, A. S., Milstein, A., Schueller, S., Hegde, R., Mangurian, C., Linos, E., 2016. Smartphone-based conversational agents and responses to questions about mental health, interpersonal violence, and physical health. *JAMA Internal Medicine*, *176*(5), 619–625.

Minsky, M. L., 1968. Semantic Information Processing. Cambridge: MIT Press.

Mirbabaie, M., Hofeditz, L., Frick, N.R. and Stieglitz, S., 2022. Artificial intelligence in hospitals: providing a status quo of ethical considerations in academia to guide future research. *AI & society*, *37*(4), pp.1361-1382.

Monett, D., Lewis, C.W. and Thórisson, K.R., 2020. Introduction to the JAGI Special Issue 'On Defining Artificial Intelligence'–Commentaries and Author's Response. *Journal of Artificial General Intelligence*, *11*(2), pp.1-100.

Montenegro, J.L.Z., da Costa, C.A. and da Rosa Righi, R., 2019. Survey of conversational agents in health. Expert Systems with Applications, 129, pp.56-67.

Morgan, D.L., 2014. Pragmatism as a paradigm for social research. *Qualitative inquiry*, *20*(8), pp.1045-1053.

Morgan, D.L., 2023. Exploring the Use of Artificial Intelligence for Qualitative Data Analysis: The Case of ChatGPT. *International Journal of Qualitative Methods*, *22*, p.16094069231211248.

Moriuchi, E., Landers, V.M., Colton, D. and Hair, N., 2021. Engagement with chatbots versus augmented reality interactive technology in e-commerce. *Journal of Strategic Marketing*, *29*(5), pp.375-389.

Morris, M.G., Venkatesh, V. and Ackerman, P.L., 2005. Gender and age differences in employee decisions about new technology: An extension to the theory of planned behavior. *IEEE transactions on engineering management*, *52*(1), pp.69-84.

Morse, J.M. and Mitcham, C., 2002. Exploring qualitatively-derived concepts: Inductive—deductive pitfalls. *International journal of qualitative methods*, *1*(4), pp.28-35.

Motger, Q., Franch, X. and Marco, J., 2022. Software-Based Dialogue Systems: Survey, Taxonomy and Challenges. *ACM Computing Surveys (CSUR)*, pp. 1-40.

Munguia, P. and Brennan, A., 2020. Scaling the Student Journey from Course-Level Information to Program Level Progression and Graduation: A Model. *Journal of Learning Analytics*, *7*(2), pp.84-94.

Mygland, M.J., Schibbye, M., Pappas, I.O. and Vassilakopoulou, P., 2021, September. Affordances in human-chatbot interaction: a review of the literature. In *Conference on e-Business, e-Services and e-Society* (pp. 3-17). Springer, Cham.

Naderifar, M., Goli, H. and Ghaljaie, F., 2017. Snowball sampling A purposeful method of sampling in qualitative research. Strides in development of medical education, 14(3), pp. 1-4.

Naeem, M., Ozuem, W., Howell, K. and Ranfagni, S., 2023. A step-by-step process of thematic analysis to develop a conceptual model in qualitative research. *International Journal of Qualitative Methods*, *22*, p.16094069231205789.

Nair, K. and Gupta, R., 2021. Application of AI technology in modern digital marketing environment. *World Journal of Entrepreneurship, Management and Sustainable Development*, 17(3), pp. 318-328.

Nanayakkara, N. W. O. K. D. S. P., 2020. Application of Artificial Intelligence in Marketing Mix: A Conceptual Review. *The Conference Proceedings of 11th International Conference on Business & Information ICBI, University of Kelaniya, Sri Lanka.* ISSN 2465-6399, pp. 530-542.

Nam, H. and Kannan, P.K., 2020. Digital environment in global markets: cross-cultural implications for evolving customer journeys. *Journal of International Marketing*, *28*(1), pp.28-47.

Nasr, M., Islam, M.M., Shehata, S., Karray, F. and Quintana, Y., 2021. Smart Healthcare in the Age of AI: Recent Advances, Challenges, and Future Prospects. *IEEE Access*, 2021, pp. 1-24.

Nass, C., Steuer, J. and Tauber, E.R., 1994, April. Computers are social actors. In *Proceedings of the SIGCHI conference on Human factors in computing system,* pp. 72-78.

Nazer, L.H., Zatarah, R., Waldrip, S., Ke, J.X.C., Moukheiber, M., Khanna, A.K., Hicklen, R.S., Moukheiber, L., Moukheiber, D., Ma, H. and Mathur, P., 2023. Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digital Health*, *2*(6), p.e0000278.

Nguyen, T.-M., Quach, S., & Thaichon, P., 2022. The effect of AI quality on customer experience and brand relationship. Journal of Consumer Behaviour, 21(3), pp. 481–493.

Nguyen, M., Casper Ferm, L.E., Quach, S., Pontes, N. and Thaichon, P., 2023. Chatbots in frontline services and customer experience: An anthropomorphism perspective. *Psychology & Marketing*. 2023. pp. 1-25.

Nickerson, R.S., 1981. Why interactive computer systems are sometimes not used by people who might benefit from them. *International Journal of Man-Machine Studies*, *15*(4), pp.469-483.

Nickerson, R. C., Varshney, U. and Muntermann, J., 2013**.** A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), pp. 336–359.

Nielsen, J. and Landauer, T.K., 1993, May. A mathematical model of the finding of usability problems. In *Proceedings of the INTERACT'93 and CHI'93 conference on Human factors in computing systems*, pp. 206-213.

Nielsen, J., 1994. *Usability engineering*. Morgan Kaufmann.

Nilsson, N.J., 2009. *The quest for artificial intelligence*. Cambridge University Press.

Nißen, M., Selimi, D., Janssen, A., Cardona, D.R., Breitner, M.H., Kowatsch, T. and von Wangenheim, F., 2022. See you soon again, chatbot? A design taxonomy to characterize user-chatbot relationships with different time horizons. *Computers in Human Behavior*, *127*, p.107043.

Noble, S.M., Mende, M., Grewal, D. and Parasuraman, A., 2022. The Fifth Industrial Revolution: How harmonious human–machine collaboration is triggering a retail and service [r] evolution. *Journal of Retailing*, 2022, pp. 1-10.

Nowak, G.J. and Phelps, J., 1994. Conceptualizing the integrated marketing communications' phenomenon: An examination of its impact on advertising practices and its implications for advertising research. *Journal of Current Issues & Research in Advertising*, *16*(1), pp.49-66.

Omoge, A.P., Gala, P. and Horky, A., 2022. Disruptive technology and AI in the banking industry of an emerging market. *International Journal of Bank Marketing*, (ahead-of-print).

Open.ai, 2022. ChatGPT: Optimizing Language Models for Dialogue [online]. Available at: https://openai.com/blog/chatgpt/ (Accessed 26 February 2023).

Open.ai, 2023. Introducing the ChatGPT app for iOS [online]. Available at: https://openai.com/blog/introducing-the-chatgpt-app-for-ios (Accessed 18 June 2023).

Orea-Giner, A., Muñoz-Mazón, A., Villacé-Molinero, T. and Fuentes-Moraleda, L., 2022. Cultural tourist and user experience with artificial intelligence: a holistic perspective from the Industry 5.0 approach. *Journal of Tourism Futures*, (ahead-of-print).

Ortagus, J.C. and Tanner, M.J., 2019. Going to college without going to campus: A case study of online student recruitment. *Innovative Higher Education*, *44*(1), pp.53-67.

Osborn, A.F., 1921. *A short course in advertising*. C. Scribner's sons.

Osborne, K., Loveder, P. and Knight, G., 2019. The Student Journey: Skilling for Life.'No Frills' Conference Discussion Paper. *National Centre for Vocational Education Research (NCVER)*.

Overgoor, G., Chica, M., Rand, W. and Weishampel, A., 2019. Letting the computers take over: Using AI to solve marketing problems. *California Management Review*, *61*(4), pp.156-185.

Owoc, M.L., Sawicka, A. and Weichbroth, P., 2019, August. Artificial intelligence technologies in education: benefits, challenges and strategies of implementation. In *IFIP International Workshop on Artificial Intelligence for Knowledge Management*, 2019, pp. 37-58.

Ozuem, W., Willis, M. and Howell, K., 2022. Thematic analysis without paradox: sensemaking and context. *Qualitative Market Research: An International Journal*, *25*(1), pp.143-157.

Ozuem, W., Ranfagni, S., Willis, M., Salvietti, G. and Howell, K., 2024. Exploring the relationship between chatbots, service failure recovery and customer loyalty: A frustration–aggression perspective. *Psychology & Marketing*, 2024, pp. 1-21.

Pantano, E. and Pizzi, G., 2020. Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services*, *55*, p.102096.

Palazón, M., López, M., Sicilia, M. and López, I., 2022. The customer journey: a proposal of indicators to evaluate integration and customer orientation. *Journal of Marketing Communications*, *28*(5), pp.528-559.

Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J.P., Duan, N. and Hoagwood, K., 2015. Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. *Administration and policy in mental health and mental health services research*, *42*, pp.533-544.

Palla, P.J., Kyriacou, E. and Zarkada, A., 2022. The effect of involvement on attitude formation and strength in the digital domain. *Journal of Marketing Communications*, pp.1-24.

Pandey, N., 2023. Future of Employer Branding in the Era of Bard, ChatGPT, Metaverse and Artificial Intelligence. *NHRD Network Journal*, *16*(3), pp.258-268.

Patel, S.B. and Lam, K., 2023. ChatGPT the future of discharge summaries. The Lancet Digital Health, 5, pp.107-108.

Patil, V., Padale, T., Waghmare, G. and Kulkarni, D., 2021. A study on understanding future of Artificial Intelligence in the various functions of marketing. *Turkish Online Journal of Qualitative Inquiry*, *12*(6).

Patton, M.Q., 2015. *Qualitative research & evaluation methods: integrating theory and practice*. Fourth. Thousand Oaks, California: SAGE Publications, Inc.

Patton, E. and Appelbaum, S. H., 2003. The Case for Case Studies in Management Research. *Management Research News*, *26*(5), pp. 60-71.

Payne, E.M., Peltier, J.W. and Barger, V.A., 2018. Mobile banking and AI-enabled mobile banking: The differential effects of technological and non-technological factors on digital natives' perceptions and behavior. *Journal of Research in Interactive Marketing*, 12(3), pp. 328-346.

Perera, C.H., Nayak, R. and Nguyen, L.T.V., 2022. The impact of social media marketing and brand credibility on higher education institutes' brand equity in emerging countries. *Journal of Marketing Communications*, pp.1-26.

Pérez, J.Q., Daradoumis, T. and Puig, J.M.M., 2020. Rediscovering the use of chatbots in education: A systematic literature review. *Computer Applications in Engineering Education*, *28*(6), pp.1549-1565.

Pérez-Marín, D., 2021. A Review of the Practical Applications of Pedagogic Conversational Agents to Be Used in School and University Classrooms. *Digital*, *1*(1), pp.18-33.

Perifanis, N.A. and Kitsios, F., 2023. Investigating the influence of artificial intelligence on business value in the digital era of strategy: A literature review. *Information*, *14*(2), p.85.

Petty, R. E. and Cacioppo, J. T., 1986. The elaboration likelihood model of persuasion. Advances in Experimental Social Psychology, 19, pp. 123-205.

Petty, R.E., 2018. Attitudes and persuasion: Classic and contemporary approaches. Routledge.

Piccolo, L.S., Mensio, M. and Alani, H., 2018, October. Chasing the chatbots. In *International Conference on Internet Science* (pp. 157-169). Springer, Cham.

Polkinghorne, D.E., 1988. *Narrative knowing and the human sciences*. Suny Press.

Poole, D.L. and Mackworth, A.K., 2010. Artificial Intelligence: foundations of computational agents. Cambridge University Press.

Porcu L, del Barrio-García S, Kitchen PJ. How Integrated Marketing Communications (IMC) works? A theoretical review and an analysis of its main drivers and effects. Communication & Society. 2012 Jan 1;25(1):313-48.

Potter, J. and Edwards, D., 2001. Discursive social psychology. *The new handbook of language and social psychology*, *9*, pp.103-118.

Pouliot, V., 2007. “Sobjectivism”: Toward a constructivist methodology. *International studies quarterly*, *51*(2), pp.359-384.

Prabowo, H., Bramulya, R. and Yuniarty, Y., 2020. Student purchase intention in higher education sector The role of social network marketing and student engagement. Management Science Letters, 10(1), pp.103-110.

Praditomo, M.A.A., Hidayanto, A.N., Stefanus, L.Y., Nugroho, W.S. and Ibrahim, R.S., 2022, August. Personal Chatbot Evaluation with Elaboration Likelihood Model on Social Messaging Application. In *2022 10th International Conference on Information and Communication Technology (ICoICT)* (pp. 211-216). IEEE.

Puccinelli, N.M., Goodstein, R.C., Grewal, D., Price, R., Raghubir, P. and Stewart, D., 2009. Customer experience management in retailing: understanding the buying process. *Journal of retailing*, *85*(1), pp.15-30.

Punj, G. and Moore, R., 2009. Information search and consideration set formation in a web-based store environment. Journal of Business Research, 62(6), pp.644-650.

Puntoni, S., Reczek, R.W., Giesler, M. and Botti, S., 2021. Consumers and artificial intelligence: An experiential perspective. *Journal of Marketing*, *85*(1), pp.131-151.

Putri, C.A. and Ginting, P., 2021. The Influence of E-Service Quality and Relational Marketing on E-Satisfaction in Using Mobile Banking through User Experience at Bank Syariah Mandiri Medan Petisah Branch Office*, International Journal of Research and Review*, 8(8), 587-596

Rai, A., 2020. Explainable AI: From black box to glass box. *Journal of the Academy of Marketing Science*, *48*(1), pp.137-141.

Raisch, S. and Krakowski, S., 2021. Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), pp.192-210.

Ramsay, R.E., 1921. *Effective direct advertising: the principles and practice of producing direct advertising for distribution by mail or otherwise*. D. Appleton.

Rasch, R., Kott, A. and Forbus, K.D., 2003. Incorporating AI into military decision making: an experiment. *IEEE Intelligent Systems*, *18*(4), pp.18-26.

Rashkova, Y., Moi, L., Marku, E. and Cabiddu, F., 2023. Online integrated marketing communication strategies of international brands: standardization vs. adaptation approaches. *Journal of Marketing Communications*, pp.1-24.

Rastegar, N., Flaherty, J., Liang, L.J. and Choi, H.S.C., 2021. The adoption of self-service kiosks in quick-service restaurants. *European Journal of Tourism Research*, *27*(1), pp. 1-23.

Rathore, B., 2023. Digital Transformation 4.0: Integration of Artificial Intelligence & Metaverse in Marketing. *Eduzone: International Peer Reviewed/Refereed Multidisciplinary Journal*, *12*(1), pp.42-48.

Ratten, V. and Jones, P., 2023. Generative artificial intelligence (ChatGPT): Implications for management educators. *The International Journal of Management Education*, *21*(3), p.100857.

Rese, A., Ganster, L. and Baier, D., 2020. Chatbots in retailers’ customer communication: How to measure their acceptance?. *Journal of Retailing and Consumer Services*, *56*, pp. 1-14.

Restivo, S. and Croissant, J., 2008. Social constructionism in science and technology studies. Handbook of constructionist research, pp.213-229.

Rishi, B. and Popli, S., 2021. Getting into the customers, shoes: customer journey management. In *Crafting Customer Experience Strategy* (pp. 21-45). Emerald Publishing Limited.

Riva, G. and Marchetti, A., 2022. Humane robotics. A multidisciplinary approach towards the development of humane-centered technologies.

Robertson, T.S., 1971. *Innovative behavior and communication*. Holt McDougal.

Robson, C. and McCartan, K. 2016. Real World Research. 4th edn. Wiley. Available at: https://www.perlego.com/book/1485149/real-world-research-pdf (Accessed 18 February 2024).

Roll, I. and Wylie, R., 2016. Evolution and revolution in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 26(2), pp.582-599.

Rudhumbu, N., 2022. Applying the UTAUT2 to predict the acceptance of blended learning by university students. Asian Association of Open Universities Journal, 17(1), pp.15-36.

Rudolph, J., Tan, S. and Tan, S., 2023. ChatGPT Bullshit spewer or the end of traditional assessments in higher education. Journal of Applied Learning and Teaching, 6(1), pp. 1-22.

Russell, S., and Norvig P., 2022 *Artificial Intelligence: A Modern Approach. Global Edition* (4th ed.). Pearson

Ryan, M. (2019). Ethics of Using AI and Big Data in Agriculture: The Case of a Large Agriculture Multinational. *ORBIT Journal*, *2*(2). https://doi.org/10.29297/orbit.v2i2.109

Sadiku, M.N., Musa, S.M. and Chukwu, U.C., 2022. *Artificial Intelligence in Education*. iUniverse, 2(1), pp. 5-11.

Saheb, T., Saheb, T. and Carpenter, D.O., 2021. Mapping research strands of ethics of artificial intelligence in healthcare: A bibliometric and content analysis. *Computers in Biology and Medicine*, *135*, p.104660.

Santos, S. and Gonçalves, H.M., 2021. The consumer decision journey: A literature review of the foundational models and theories and a future perspective. *Technological Forecasting and Social Change*, *173*, pp. 1-14.

Saura, J.R., 2021. Using data sciences in digital marketing: Framework, methods, and performance metrics. *Journal of Innovation & Knowledge*, *6*(2), pp.92-102.

Savin-Baden, M. and Van Niekerk, L., 2007. Narrative Inquiry: Theory and Practice, Journal of Geography in Higher Education, 31:3, pp. 459-472.

Saunders, M., Lewis, P. and Thornhill, A., 2019. *Research methods for business students*. Pearson education.

Schmager, S., Grøder, C.H., Parmiggiani, E., Pappas, I. and Vassilakopoulou, P., 2024. Exploring citizens' stances on AI in public services: A social contract perspective. *Data & Policy*, *6*, p.e19.

Schmitt, B. 1999. Experiential marketing. Journal of Marketing Management, 15(1–3), pp. 53–67.

Schultz, D.E., 1992. Integrated marketing communications. *Journal of Promotion Management*, *1*(1), pp.99-104.

Schwandt, T.A., 2003. Three epistemological stances for qualitative inquiry: Interpretivism, hermeneutics, and social constructionism. In *Handbook of qualitative research* (pp. 189-213). SAGE Publishing.

Schwartz, H.A. and Ungar, L.H., 2015. Data-driven content analysis of social media: A systematic overview of automated methods. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), pp.78-94.

Schwieger, D. and Ladwig, C., 2018. Reaching and retaining the next generation Adapting to the expectations of Gen Z in the classroom. Information Systems Education Journal, 16(3), p.45.

Scott, D.M., 2022. *The new rules of marketing and PR: How to use content marketing, podcasting, social media, AI, live video, and newsjacking to reach buyers directly*. John Wiley & Sons.

Scriven, M., 1991. Prose and cons about goal-free evaluation. *Evaluation Practice*, *12*(1), pp.55-62.

Searle, J.R., 1995. The construction of social reality. Simon and Schuster.

Senyapar, H.N.D., 2024. Artificial Intelligence in Marketing Communication: A Comprehensive Exploration of the Integration and Impact of AI. *Technium Social Sciences Journal*, *55*, pp.64-81.

Shani, C., Libov, A., Tolmach, S., Lewin-Eytan, L., Maarek, Y. and Shahaf, D., 2021. " Alexa, what do you do for fun?" Characterizing playful requests with virtual assistants. *arXiv preprint arXiv:2105.05571*.

Shankar, V. and Parsana, S., 2022. An overview and empirical comparison of natural language processing (NLP) models and an introduction to and empirical application of autoencoder models in marketing. *Journal of the Academy of Marketing Science*, pp.1-27.

Shavitt, S. and Barnes, A.J., 2020. Culture and the consumer journey. Journal of Retailing 96(1), pp. 40–54.

Sheldon, A.F., 1911. *The Art of Selling: For Business Colleges, High Schools of Commerce, YMCA Classes and Private Students*. Sheldon school.

Shukla, N., Kolbeinsson, A., Otwell, K., Marla, L. and Yellepeddi, K., 2019, July. Dynamic pricing for airline ancillaries with customer context. In *Proceedings of the 25th ACM SIGKDD International Conference on knowledge discovery & data mining*, 2019, pp. 2174-2182.

Schumann, D.W., Kotowski, M.R., Ahn, H.Y. and Haugtvedt, C.P., 2012. The elaboration likelihood model. *Advertising theory*, *1*, pp.51-68.

Siala, H. and Wang, Y., 2022. SHIFTing artificial intelligence to be responsible in healthcare: A systematic review. *Social Science & Medicine*, 2022, p.114782.

Sikström, P., Valentini, C., Kärkkäinen, T. and Sivunen, A., 2022. How pedagogical agents communicate with students: A two-phase systematic review. *Computers & Education*, 2022, p.104564.

Simon, H.A., 1957. A behavioral model of rational choice. *Models of man, social and rational: Mathematical essays on rational human behavior in a social setting*, pp.241-260.

Singh, G. and Atta, S., 2021. Recommendations for implementing VR and AR in Education, Art, and Museums. *ResearchBerg Review of Science and Technology*, *1*(1), pp.16-40.

Singh, J., Nambisan, S., Bridge, R.G. and Brock, J.K.U., 2021. One-voice strategy for customer engagement. *Journal of Service Research*, *24*(1), pp.42-65.

Sinwar, D., Dhaka, V.S., Sharma, M.K. and Rani, G., 2020. AI-based yield prediction and smart irrigation. In *Internet of Things and Analytics for Agriculture, (2)*, pp. 155-180.

Sitzmann, T. and Weinhardt, J.M., 2019. Approaching evaluation from a multilevel perspective: A comprehensive analysis of the indicators of training effectiveness. *Human Resource Management Review*, *29*(2), pp.253-269.

Smith, C., 2010. *What is a person?: Rethinking humanity, social life, and the moral good from the person up*. University of Chicago Press.

Smith, C., McGuire, B., Huang, T. and Yang, G., 2006. The history of artificial intelligence. *University of Washington*, *27*.

Smutny, P. and Schreiberova, P., 2020. Chatbots for learning: A review of educational chatbots for the Facebook Messenger. *Computers & Education*, *151*, p.1 - 11.

Softić, A., Husić, J.B., Softić, A. and Baraković, S., 2021, March. Health chatbot: design, implementation, acceptance and usage motivation. In *2021 20th International Symposium INFOTEH-JAHORINA (INFOTEH),* pp. 1-6.

Song, C.S. and Kim, Y.K., 2021. Predictors of consumers' willingness to share personal information with fashion sales robots. *Journal of Retailing and Consumer Services*, *63*, pp. 1-10.

Song, C.S. and Kim, Y.K., 2022. The role of the human-robot interaction in consumers' acceptance of humanoid retail service robots. *Journal of Business Research*, *146*, pp.489-503.

Soobrayan, V., 2003. Ethics, truth and politics in constructivist qualitative research. Westminster Studies in Education, 26(2), pp.107-123.

Stark, L. and Hoey, J., 2021, March. The ethics of emotion in artificial intelligence systems. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, pp. 782-793.

Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., Laughlin, P., Machtynger, J. and Machtynger, L., 2020. Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. *The Bottom Line*, *33*(2), pp.183-200.

Strycharz, J., van Noort, G., Helberger, N. and Smit, E., 2019. Contrasting perspectives–practitioner's viewpoint on personalised marketing communication. European Journal of Marketing, 53(4), pp.635-660.

Sudiatmika, I.P. and Ariantini, M., 2021, August. Digital Marketing Chatbot Using API Dialog Flow Case Studi ITB Stikom Bali, Jimbaran Campus. In *Proceedings of The 6th Asia-Pacific Education And Science Conference, AECon 2020, 19-20 December 2020, Purwokerto, Indonesia*.

Surendro, K., 2019, March. Predictive analytics for predicting customer behavior. In *2019 International Conference of Artificial Intelligence and Information Technology (ICAIIT),* pp. 230-233.

Szczepanski, C.M., 2006. *General and special interest magazine advertising and the elaboration likelihood model: a comparative content analysis and investigation of the effects of differential route processing execution strategies*. State University of New York at Buffalo.

Tafesse, W. and Kitchen, P.J., 2017. IMC–an integrative review. *International Journal of Advertising*, *36*(2), pp.210-226.

Talaviya, T., Shah, D., Patel, N., Yagnik, H. and Shah, M., 2020. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, pp.58-73.

Thomaz, F., Salge, C., Karahanna, E. and Hulland, J., 2020. Learning from the dark web: Leveraging conversational agents in the era of hyper-privacy to enhance marketing. *Journal of the Academy of Marketing Science*, *48*(1), pp.43-63.

Ting, I.H., Yen, C.S. and Yang, S.C., 2021, November. RPA as A Tool for Social Media Marketing: The good, The Bad and The Ugly. In *Proceedings of the 8th Multidisciplinary International Social Networks Conference* (pp. 49-52).

Tong, S., Luo, X. and Xu, B., 2020. Personalized mobile marketing strategies. *Journal of the Academy of Marketing Science*, *48*(1), pp.64-78.

Trivedi, J., 2019. Examining the customer experience of using banking chatbots and its impact on brand love: The moderating role of perceived risk. *Journal of Internet Commerce*, *18*(1), pp.91-111.

Tsai, Y.T. and Tiwasing, P., 2021. Customers’ intention to adopt smart lockers in last-mile delivery service: A multi-theory perspective. *Journal of Retailing and Consumer Services*, *61*, pp. 1-9.

Tueanrat, Y., Papagiannidis, S. and Alamanos, E., 2021. Going on a journey: A review of the customer journey literature. *Journal of Business Research*, *125*, pp.336-353.

Turing, A., 1950. Computing Machinery and Intelligence, *Mind*, 59(236), 433–460.

Tuten, T.L. and Hanlon, A., 2022. Introduction to Social Media Marketing. *The SAGE Handbook of Social Media Marketing*

Ungerman, O. and Dědková, J., 2019. Marketing innovations in Industry 4.0 and their impacts on current enterprises. *Applied Sciences*, *9*(18), p.3685.

Vaishya, R., Javaid, M., Khan, I.H. and Haleem, A., 2020. Artificial Intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews*, *14*(4), pp.337-339.

Vakulenko, Y., Shams, P., Hellström, D. and Hjort, K., 2019. Online retail experience and customer satisfaction: the mediating role of last mile delivery. *The International Review of Retail, Distribution and Consumer Research*, *29*(3), pp.306-320.

Vallerand, R.J., 1997. Toward a hierarchical model of intrinsic and extrinsic motivation. In *Advances in experimental social psychology*, 29, pp. 271-360. Academic Press.

van den Bosch, K. and Bronkhorst, A., 2018. Human-AI cooperation to benefit military decision making. NATO.

van Dis, E.A., Bollen, J., Zuidema, W., van Rooij, R. and Bockting, C.L., 2023. ChatGPT five priorities for research. Nature, 614(7947), pp.224-226.

Vanjani, M., Aiken, M. and Park, M., 2019. Chatbots for multilingual conversations. *Journal of Management Science and Business Intelligence*, *4*(1), pp.19-24.

Vassos, S., Malliaraki, E., Falco, F.D., Maggio, J.D., Massimetti, M., Nocentini, M.G. and Testa, A., 2016, November. Art-bots: Toward chat-based conversational experiences in museums. In *International Conference on Interactive Digital Storytelling*, pp. 433-437. Springer, Cham.

Vázquez, S., Muñoz-García, Ó., Campanella, I., Poch, M., Fisas, B., Bel, N. and Andreu, G., 2014. A classification of user-generated content into consumer decision journey stages. *Neural Networks*, *58*, pp.68-81.

Vázquez-Cano, E., Mengual-Andrés, S. and López-Meneses, E., 2021. Chatbot to improve learning punctuation in Spanish and to enhance open and flexible learning environments. *International Journal of Educational Technology in Higher Education*, *18*(1), pp.1-20.

Venkatesh, V. and Davis, F.D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), pp.186-204.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D., 2003. User acceptance of information technology Toward a unified view. MIS quarterly, pp.425-478.

Venkatesh, V., Thong, J.Y. and Xu, X., 2012. Consumer acceptance and use of information technology extending the unified theory of acceptance and use of technology. MIS quarterly, pp.157-178.

Venkatesh, V., 2022. Adoption and use of AI tools a research agenda grounded in UTAUT. Annals of Operations Research, pp.1-12.

Verma, S., Sharma, R., Deb, S. and Maitra, D., 2021. Artificial intelligence in marketing: Systematic review and future research direction. *International Journal of Information Management Data Insights*, *1*(1), p.100002.

Vishnoi, L., 2020. *Conversational agent: A more assertive form of chatbots [online].*Available at: https://towardsdatascience.com/conversational-agent-a-more-assertive-form-of-chatbots (Accessed 01 July 2022).

Vlačić, B., Corbo, L., e Silva, S.C. and Dabić, M., 2021. The evolving role of artificial intelligence in marketing: A review and research agenda. *Journal of Business Research*, *128*, pp.187-203.

Vollrath, M.D. and Villegas, S.G., 2022. Avoiding digital marketing analytics myopia: revisiting the customer decision journey as a strategic marketing framework. *Journal of Marketing Analytics*, *10*(2), pp.106-113.

Vrontis, D., El Nemar, S., Ouwaida, A. and Shams, S.R., 2018. The impact of social media on international student recruitment: the case of Lebanon. *Journal of International Education in Business*. 11 (1), pp. 79-103.

Wahde, M. and Virgolin, M., 2022. Conversational agents: Theory and applications. In *HANDBOOK ON COMPUTER LEARNING AND INTELLIGENCE: Volume 2: Deep Learning, Intelligent Control and Evolutionary Computation*, pp. 497-544.

Wang, P., Liu, K. and Dougherty, Q., 2018. Conceptions of artificial intelligence and singularity. *Information*, *9*(4), p.79.

Wang, C., Teo, T.S. and Janssen, M., 2021. Public and private value creation using artificial intelligence: An empirical study of AI voice robot users in Chinese public sector. *International Journal of Information Management*, *61*, p.102401.

Wang, Y., Kang, Q., Zhou, S., Dong, Y. and Liu, J., 2022. The impact of service robots in retail: Exploring the effect of novelty priming on consumer behavior. *Journal of Retailing and Consumer Services*, *68*, pp.1-15.

Wang, X., Lin, X. and Shao, B., 2022. How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management*, *66*, p.102535.

Weaver, M., 2013. Student Journey Work: A Review of Academic Library Contributions to Student Transition and Success, New Review of Academic Librarianship, 19:2, pp. 101-124,

Wedel, M., Bigné, E. and Zhang, J., 2020. Virtual and augmented reality: Advancing research in consumer marketing. *International Journal of Research in Marketing*, *37*(3), pp.443-465.

Wei, C., Yu, Z. and Fong, S., 2018, February. How to build a chatbot: chatbot framework and its capabilities. In *Proceedings of the 2018 10th International Conference on Machine Learning and Computing*, pp. 369-373.

Weizenbaum, J., 1966. ELIZA—a computer program for the study of natural language communication between man and machine. Commun. ACM. 9, pp. 36–45.

Welsh, R., 2019. Defining artificial intelligence. *SMPTE Motion Imaging Journal*, *128*(1), pp. 26-32.

Wen, L., Lin, W. and Guo, M., 2022. Study on optimization of marketing communication strategies in the era of artificial intelligence. *Mobile Information Systems*, *2022*(1), p.1604184.

Wendt, A., 1999. Social Theory of International Politics. New York: Cambridge University Press.

Wijaya, B.S., 2015. The development of hierarchy of effects model in advertising. *International Research Journal of Business Studies*, *5*(1), pp. 73-85.

Winkler, R. and Söllner, M., 2018. Unleashing the potential of chatbots in education: A state-of-the-art analysis. In *Academy of Management Annual Meeting (AOM)*. Chicago, USA. pp. 1-40.

Wirth, N., 2018. Hello marketing, what can artificial intelligence help you with. International Journal of Market Research, 60 (5), pp. 435–438.

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S. and Martins, A., 2018. Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), pp.907-931.

Wolbers, K., and Walter, N., 2021. "Silence Is Silver, but Speech Is Golden: Intelligent Voice Assistants (IVAs) and Their Impact on a Brand's Customer Decision Journey with a Special Focus on Trust and Convenience–A Qualitative Consumer Analysis in the Netherlands." *IUP Journal of Brand Management* 18, no. 1: 7-31.

Wolfe, H.D., Brown, J.K. and Thompson, G.C., 1962. Measuring Advertising Results (New York: National Industrial Conference Board, 1962). *Wolfe Measuring Advertising Results1962*.

Wong, L.W., Tan, G.W.H., Hew, J.J., Ooi, K.B. and Leong, L.Y., 2022. Mobile social media marketing a new marketing channel among digital natives in higher education. Journal of Marketing for Higher Education, 32(1), pp.1

Wu, E.H.K., Lin, C.H., Ou, Y.Y., Liu, C.Z., Wang, W.K. and Chao, C.Y., 2020. Advantages and constraints of a hybrid model K-12 E-Learning assistant chatbot. *Ieee Access*, *8*, pp.77788-77801.

Wu, C.G. and Ho, J.C., 2022. The influences of technological characteristics and user beliefs on customers' perceptions of live chat usage in mobile banking. *International Journal of Bank Marketing*, 40(1), pp. 68 – 86.

Wuenderlich, N.V. and Paluch, S., 2017. A nice and friendly chat with a bot: User perceptions of AI-based service agents. *ICIS 2017 Proceedings. 11.*

Wutz, M., Hermes, M., Winter, V. and Köberlein-Neu, J., 2023. Factors influencing the acceptability, acceptance, and adoption of conversational agents in health care: integrative review. *Journal of Medical Internet Research*, *25*, p.e46548.

Xie, L., Li, D. and Keh, H.T., 2020. Customer participation and well-being: the roles of service experience, customer empowerment and social support. *Journal of Service Theory and Practice*, *30*(6), pp.557-584.

Yan, R., 2018. " Chitty-Chitty-Chat Bot": Deep Learning for Conversational AI. In *IJCAI*, 18, pp. 5520-5526.

Yang, G., 2006. The history of artificial intelligence: AI winter and its lessons. *University of Washington (Dec. 2006)*.

Yang, S. and Evans, C., 2019. Opportunities and challenges in using AI chatbots in higher education. In *Proceedings of the 2019 3rd International Conference on Education and E-Learning,* pp. 79-83.

Yawised, K., Apasrawirote, D. and Boonparn, C., 2022. From traditional business shifted towards transformation: The emerging business opportunities and challenges in 'Metaverse' era., INCBAA, 2022, pp. 162-175.

Yin, R. K., 2009. *Case Study Research: Design and Methods* (4th ed.). Thousand Oaks, CA: Sage.

Yoon, V.Y., Hostler, R.E., Guo, Z. and Guimaraes, T., 2013. Assessing the moderating effect of consumer product knowledge and online shopping experience on using recommendation agents for customer loyalty. *Decision Support Systems*, *55*(4), pp.883-893.
Young, R.A. and Collin, A., 2004. Introduction Constructivism and social constructionism in the career field. Journal of vocational behavior, 64(3), pp.373-388.

Zanker, M., Rook, L. and Jannach, D., 2019. Measuring the impact of online personalisation: Past, present and future. *International Journal of Human-Computer Studies*, *131*, pp.160-168.

Zhai, C. and Wibowo, S., 2023. A systematic review on artificial intelligence dialogue systems for enhancing English as foreign language students' interactional competence in the university. *Computers and Education: Artificial Intelligence*, *4*, p.100134.

Zhang, C. and Lu, Y., 2021. Study on artificial intelligence: The state of the art and future prospects. *Journal of Industrial Information Integration*, *23*, p. 100224.

Zhang, D., Maslej, N., Brynjolfsson, E., Etchemendy, J., Lyons, T., Manyika, J., Ngo, H., Niebles, J.C., Sellitto, M., Sakhaee, E., Shoham, Y., Clark, J., Perrault, R., 2022. "The AI Index 2022 Annual Report," AI Index Steering Committee, *Stanford Institute for Human-Centered AI, Stanford University*

Zhang, H., Wu, C., Xie, J., Kim, C. and Carroll, J.M., 2023. QualiGPT: GPT as an easy-to-use tool for qualitative coding. *arXiv preprint arXiv:2310.07061*.

Zhang, H., Wu, C., Xie, J., Lyu, Y., Cai, J. and Carroll, J.M., 2023a. Redefining qualitative analysis in the AI era: Utilizing ChatGPT for efficient thematic analysis. *arXiv preprint arXiv:2309.10771*.

Zhao, H., Kelly, A., Hulusic, V. and Charles, F., 2021. The Application of Virtual Reality in Student Recruitment. In *Proceedings of the 27th ACM Symposium on Virtual Reality Software and Technology,* pp. 1-2.

Zhao, M., 2023. The Emotion Recognition in Psychology of Human-robot Interaction. *Psychomachina*, *1*, pp.1-11.

Zhu, Y., Janssen, M., Wang, R. and Liu, Y., 2021. It Is Me, Chatbot: Working to Address the COVID-19 Outbreak-Related Mental Health Issues in China. User Experience, Satisfaction, and Influencing Factors. *International Journal of Human–Computer Interaction*, 2021, pp.1-13.

Zhu, Y., Wang, R. and Pu, C., 2022. "I am chatbot, your virtual mental health adviser." What drives citizens' satisfaction and continuance intention toward mental health chatbots during the COVID-19 pandemic? An empirical study in China. *Digital Health*, *8*, pp. 1-15.

Zumstein, D. and Hundertmark, S., 2017. CHATBOTS--AN INTERACTIVE TECHNOLOGY FOR PERSONALIZED COMMUNICATION, TRANSACTIONS AND SERVICES. *IADIS International Journal on WWW/Internet*, *15*(1), pp. 96-109.

APPENDICES

Appendix 1 – Taxonomies of CAs

Author (Year)	Key Concept	Perspective	Number of Dimensions	Characteristics	Theoretical Framework
Gnewuch et al. (2017)	1. Framework for design of cooperative and social conversational agents for customer service 2. Research Question: *How to design cooperative and social conversational agents to increase service quality in customer service?*	Customer Service in any industry – museums, healthcare, e-commerce,	2	*Context* – General Purpose/Specific Domain *Mode of comm.* – text-based/speech based	• The cooperative principle of conversation (Grice,1975) • Social response theory (Nass et al., 2000)
Følstad et al. (2018)	1. Chatbot typology for understanding interaction design 2. Proposed are 4 archetypes: a) Customer support b) Personal Assistant c) Content Curation d) Coach	Interaction design for any industry	2	*Locus of control* – Chatbot-driven dialogue/User-driven dialogue *Duration of Relation* – Short-term relation/Long-term Relation	Collier et al. (2012) three-step template for typology development. a) Outline general concept b) Identify key dimensions c) Cross-tabulate dimensions
Feine et al. (2019)	Taxonomy based on social cues of communication	Interdisciplinary design providing a bridge between different research fields	4	*Verbal Cues – content, style* *Visual Cues – kinesics, proxemics, agent appearance, CMC* *Auditory Cues – voice set,*	• Computers as Social Actors Paradigm • Interpersonal Communications Theory

				voice qualities, vocalisation *Invisible Cues – Chronemics, haptics*	
Diedreich et al. (2019)	Taxonomy of platforms for conversational agents	The design and capabilities of the CAs platform for any industry or use case	11	*Communication mode* Text-based Speech-based Both *Context* General-purpose Domain-specific *Language* Single language Multi language *Intelligence* Rule-based Self-learning *Implementation* Programming Modelling Supervised learn. Hybrid *Hosting* On-premise Cloud Both *Pricing model* Usage-based User-based Instance-based Free *Reporting* Without reporting With reporting *Sentiment detection* Without sentiment With sentiment *Enterprise integration* None Application programming interface Pre-build interface(s)	Nickerson et al. (2013) model for developing taxonomies

				Platform integration Single-platform Cross-platform	
Janssen et al. (2020a)	Taxonomy of virtual assistants in any context: design elements for domain-specific Chatbots	3 perspectives – intelligence, interaction, context	17	D_1 Intelligence framework $C_{1,1}$ Rule-based system $C_{1,2}$ Utility-based system $C_{1,3}$ Model-based system $C_{1,4}$ Goal-based system $C_{1,5}$ Self-learning system D_2 Intelligence quotient $C_{2,1}$ Only rule-based knowledge $C_{2,2}$ Text understanding $C_{2,3}$ Text understanding and further abilities D_3 Personality processing $C_{3,1}$ Principal self $C_{3,2}$ Adaptive self D_4 Socio-emotional behavior $C_{4,1}$ Not present $C_{4,2}$ Present D_5 Service integration $C_{5,1}$ None $C_{5,2}$ Single integration $C_{5,3}$ Multiple integration D_6 Multimodality $C_{6,1}$ Unidirectional $C_{6,2}$ Bidirectional D_7 Interaction classification $C_{7,1}$ Graphical $C_{7,2}$ Interactive	Nickerson et al. (2013) model for developing taxonomies

				D_8 Interface personification $C_{8,1}$ Disembodied $C_{8,2}$ Embodied D_9 User assistance design $C_{9,1}$ Reactive assistance $C_{9,2}$ Proactive assistance D_{10} Number of participants $C_{10,1}$ Individual human participant $C_{10,2}$ Two or more human participants D_{11} Additional human support $C_{11,1}$ No $C_{11,2}$ Yes D_{12} Front-end user interface channel $C_{12,1}$ App $C_{12,2}$ Collaboration and communication tools $C_{12,3}$ Social media $C_{12,4}$ Website $C_{12,5}$ Multiple D_{13} Chatbot role $C_{13,1}$ Facilitator $C_{13,2}$ Peer $C_{13,3}$ Expert D_{14} Relation duration $C_{14,1}$ Short-term relation $C_{14,2}$ Long-term relation D_{15} Application domain $C_{15,1}$ E-customer service $C_{15,2}$ Daily life $C_{15,3}$ E-commerce $C_{15,4}$ E-learning $C_{15,5}$ Finance $C_{15,6}$ Work and career D_{16} Collaboratio	

				n goal $C_{16,1}$ Non goal-oriented $C_{16,2}$ Goal-oriented D_{17} Motivation for chatbot use $C_{17,1}$ Productivity $C_{17,2}$ Entertainment $C_{17,3}$ Social/relational $C_{17,4}$ Utility	
Janssen et al. (2020b)	A taxonomy of business-to-business chatbots in customer services	B2B customer service	17	**Industry classification** $C_{1,1}$ Financial services industry (5%) $C_{1,2}$ Manufacturing industry (22%) $C_{1,3}$ Marketing industry (10%) $C_{1,4}$ Software industry (63%) **D_2 Business integration** $C_{2,1}$ No (68%) $C_{2,2}$ Yes (32%) **D_3 Access to business data** $C_{3,1}$ No (90%) $C_{3,2}$ Yes (10%) **D_4 Dialogue structure** $C_{4,1}$ Predefined (48%) $C_{4,2}$ Open (15%) $C_{4,3}$ Both (37%) **D_5 Data policy** $C_{5,1}$ Not provided (65%) $C_{5,2}$ Provided (35%) **D_6 Handoff to human agent** $C_{6,1}$ Not possible (12%) $C_{6,2}$ Possible (88%) **D_7 Small talk** $C_{7,1}$ Not possible (80%) $C_{7,2}$ Possible (20%) **D_8 Human-like avatar** $C_{8,1}$ No (90%) $C_{8,2}$ Yes (10%) **D_9 Content related service** $C_{9,1}$ Content advertisement (70%) $C_{9,2}$ Content consumption (30%) **D_{10} Account authentication** $C_{10,1}$ Not required (63%) $C_{10,2}$ Optional (12%) $C_{10,3}$ Required (25%) **D_{11} Question personalization** $C_{11,1}$ None (12%) $C_{11,2}$ FAQ (50%) $C_{11,3}$ Personalized account questions (30%) $C_{11,4}$ Highly personalized questions (8%) **D_{12} Customer service orientation** $C_{12,1}$ Knowledge-	Nickerson et al. (2013) model for developing taxonomies

				oriented (53%) $C_{12,2}$ Task-oriented (47%) ***D_{13}* Company information** *$C_{13,1}$* No (70%) *$C_{13,2}$* Yes (30%) ***D_{14}* Service/product information** *$C_{14,1}$* No (15%) *$C_{14,2}$* Yes (85%) ***D_{15}* Pricing** *$C_{15,1}$* No (80%) *$C_{15,2}$* Yes (20%) ***D_{16}* Action request** *$C_{16,1}$* Book/show a demo (8%) *$C_{16,2}$* Callback request (32%) *$C_{16,3}$* Both (35%) *$C_{16,4}$* None (25%) ***D_{17}* Service request** *$C_{17,1}$* Support question /ticket (32%) *$C_{17,2}$* Billing details (3%) *$C_{17,3}$* User management (3%) *$C_{17,17}$* Multiple (10%) *$C_{17,5}$* None (52%)	
Nißen et al. (2022)	Taxonomy of CAs determined by their temporal profiles	Taxonomy that is driven by the user-chatbot relationship with different time horizons as foundational characteristic using 3 layers and 5 perspectives	22	**Temporal Profile** D_1 Time horizon $C_{1,1}$ Short-term $C_{1,2}$ Medium-term $C_{1,3}$ Long-term $C_{1,4}$ Lifelong D_2 Frequency of interactions $C_{2,1}$ One-time only $C_{2,2}$ Multiple times D_3 Duration of interactions $C_{3,1}$ Short 51 $C_{3,2}$ Medium $C_{3,3}$ Long D_4 Consecutiveness of interactions $C_{4,1}$ Unrelated $C_{4,2}$ Related D_5 Role $C_{5,1}$ Expert $C_{5,2}$ Facilitator $C_{5,3}$ Peer D_6 Communication style $C_{6,1}$ Task-oriented $C_{6,2}$ Socially-/chat-oriented D_7 Avatar representation $C_{7,1}$ Disembodied $C_{7,2}$ **Intelligence** D_8 Intelligence framework $C_{8,1}$ Rule-based 59 $C_{8,2}$ Hybrid $C_{8,3}$ Artificially intelligent D_9 Intelligence quotient $C_{9,1}$ Rule-based knowledge only $C_{9,2}$ Text understanding $C_{9,3}$ Text understanding+ D_{10} Personality adaptability $C_{10,1}$ Principal self $C_{10,2}$ Adaptive self D_{11} Socio-emotional behavior $C_{11,1}$ Not present $C_{11,2}$ Present	Nickerson et al. (2013) model for developing taxonomies

				D_{12} Service integration $C_{12,1}$ None $C_{12,2}$ External data $C_{12,3}$ Media resources $C_{12,4}$ Multiple **Interaction** D_{13} Front-end user interface $C_{13,1}$ Application $C_{13,2}$ Social media $C_{13,3}$ Collaboration tools $C_{13,4}$ Website $C_{13,5}$ Various D_{14} Communication Modality $C_{14,1}$ Text $C_{14,2}$ Text + voice D_{15} Interaction Modality $C_{15,1}$ Graphical $C_{15,2}$ Interactive D_{16} User assistance design $C_{16,1}$ Reactive $C_{16,2}$ Proactive $C_{16,3}$ Reciprocal D_{17} Personalization $C_{17,1}$ Static $C_{17,2}$ Adaptive D_{18} Add. Human support $C_{18,1}$ No $C_{18,2}$ Yes D_{19} Gamification $C_{19,1}$ No$C_{19,2}$ Yes **Context** D_{20} Application Domain $C_{20,1}$ Business $C_{20,2}$ Education $C_{20,3}$ Healthcare $C_{20,4}$ Daily Life D_{21} Motivation/purpose $C_{21,1}$ Productivity $C_{21,2}$ Entertainment $C_{21,3}$ Utility $C_{21,4}$ Informational $C_{21,5}$ Coaching D_{22} Collaboration goal $C_{22,1}$ Not goal-oriented $C_{22,2}$ Goal-oriented	

Appendix 1: Taxonomies of CAs (Source: Author, 2024)

Appendix 2 – Consumer Journey models

Author (year)	Model Name	Model Stages (pre-purchase)						Stages (post-purchase)
Lewis (1898)	AID	Attention	Interest	Desire				
Lewis (1900)	AIDA	Attention	Interest	Desire	Action			
Printers Ink Editorial (1910)	AICA	Attention	Interest	Conviction	Action			
Sheldon (1911)	AIDAS	Attention	Interest	Desire	Action			Satisfaction
Hall (1915)	AICCA	Attention	Interest	Confidence	Conviction	Action		
Ramsay (1921)	AIDCA	Attention	Interest	Desire	Caution	Action		
Kitson (1921)	AIDCA	Attention	Interest	Desire	Conviction	Action		
Osborn (1921)	AIJA	Attention	Interest	Judgement	Action			
Bedell (1940)	AIDCA	Attention	Interest	Desire	Conviction	Action		
Devoe (1956)	AIDMA	Attention	Interest	Desire	Memory	Action		
Lavidge and Steiner (1961)	AKLPCP	Awareness	Knowledge	Liking	Preference	Conviction	Purchase	
Colley (1961)	ACCA	Awareness	Comprehension	Conviction	Action			
Advertising Research Foundation (1961)	EPCCA	Exposure	Perception	Communication (Knowledge)	Communication (Attitude)	Action		
Wolfe, Brown, Thompson (1962)	AAPIS	Awareness	Acceptance	Preference	Intention	Sale		
Rogers (1962)	AIETA	Awareness	Interest	Evaluation	Trial	Adoption		
Robertson (1971)	ACALTA	Awareness	Comprehension	Attitude	Legitimation	Trial	Adoption	
McGuire (1978)	PACYRB	Presentation	Attention	Comprehension	Yielding	Retention		Behaviour
Puccinelli et al. (2009)		Need Recognition	Information Search	Evaluation	Purchase			Post Purchase
Wijaya (2015)	AISDALSLove	Attention	Interest	Search	Desire	Action		Like/Dislike Share Love/Hate
Lemon and Verhoef (2016)	PPP	Pre- Purchase	Purchase					Post-Purchase
Colicev et al. (2018)	APS	Awareness	Purchase Intent					Satisfaction
Demmers et al. (2020)	PCP	Pre-consumption	Consumption					Post - Consumption
Kim, Jiang and Bruce (2021)	LFD	Learn	Feel	Do				

Appendix 2: Consumer Journey models (Source: Author, 2024)