# A STUDY ON THE MOTIVATIONS AND CHALLENGES IN THE ADOPTION OF VIRTUAL AGENTS IN SERVICES SECTOR

by

Venkatesh Nambakkam Jayakumar

DISSERTATION

Presented to the Swiss School of Business and Management Geneva

In Partial Fulfillment

Of the Requirements

For the Degree

DOCTOR OF BUSINESS ADMINISTRATION

SWISS SCHOOL OF BUSINESS AND MANAGEMENT GENEVA

MARCH 2024

**A STUDY ON THE MOTIVATIONS AND CHALLENGES IN THE ADOPTION OF VIRTUAL AGENTS IN SERVICES SECTOR**

by

Venkatesh Nambakkam Jayakumar

Supervised by

Prof. Kishore Kunal

APPROVED BY

______________________________

Dissertation chair

RECEIVED/APPROVED BY:

______________________________

Admissions Director

# ABSTRACT

A STUDY ON THE MOTIVATIONS AND CHALLENGES IN THE ADOPTION OF VIRTUAL AGENTS IN SERVICES SECTOR

This expanded analysis delves into the dynamics of integrating virtual agents within the services sector, focusing on understanding industry adoption through the lens of two theoretical frameworks: the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Threat Avoidance Model (TTAT). By examining responses from 628 participants, this study highlights the dual role of perceived threats as obstacles and the positive influence of effort expectancy and social norms as facilitators in the adoption process. The research underlines the importance of these factors in shaping individual attitudes and behaviours towards virtual agents. It emphasizes that addressing concerns about threats, improving the ease of use, and capitalizing on social influences can significantly enhance the adoption rates of virtual agents. Recommendations stress the necessity of refining the user experience, fortifying security measures, and strategically employing social influence to cultivate an environment more conducive to the integration of virtual agents in service-oriented sectors. This comprehensive approach aims to offer actionable insights for stakeholders looking to navigate the complexities of technology adoption and optimize the deployment of virtual agents in their operations.



***Keywords:*** Virtual Agents, Chatbots, AI, UTAUT.

## TABLE OF CONTENTS

## LIST OF TABLES

## LIST OF FIGURES

# Chapter I - Introduction

## 1.1 Introduction

Virtual agents, encompassing virtual assistants and chatbots, are sophisticated software programs engineered to emulate conversational exchanges with human users across multiple communication mediums, including text, voice, and visual interfaces (Ling et al., 2021). These agents are devised to offer automated assistance, adeptly understanding and responding to user inquiries in a manner reflective of human interaction. Their application spans a diverse range of domains, such as customer support, information retrieval, and task automation, enhancing human-computer interaction efficiencies (Priya & Sharma, 2023).

The foundation of these virtual agents lies in the integration of advanced technologies like artificial intelligence (AI), natural language processing (NLP), and machine learning. These technologies empower the agents to interpret and generate responses that closely mimic human communication (Alanzi et al., 2023). Implemented across various platforms, including websites, messaging applications, mobile apps, and smart devices, virtual agents are pivotal in augmenting user experiences by providing prompt and efficient assistance (Wutz et al., 2023).

Virtual agents are powered by a confluence of cutting-edge technologies, each playing a pivotal role in their functionality. Artificial Intelligence (AI) serves as the foundational framework, enabling these agents to exhibit intelligent and adaptive behaviours, akin to human-like interactions (Nye & Silverman, 2013). Natural Language Processing (NLP) technology is crucial, as it allows virtual agents to process and understand human languages, facilitating meaningful dialogue between the agent and users (Ling et al., 2021). Machine Learning (ML) algorithms empower these agents with the ability to learn from data over time, enhancing their interaction capabilities (Priya & Sharma, 2023).

Speech recognition technology is indispensable for voice-operated virtual agents, converting spoken words into text for further processing (Deventer & Zidda, 2023). Dialog management systems ensure the maintenance of conversational context, enabling virtual agents to follow the thread of conversations accurately (Parenti et al., 2021). Knowledge base integration allows virtual agents to access and retrieve information from vast databases, ensuring responses are informed and accurate (Etemad-Sajadi, 2014).

Additionally, Application Programming Interfaces (APIs) facilitate the seamless integration of virtual agents with external services and databases, broadening their utility and functionality (Benbasat & Wang, 2005). CHATGPT, a specific AI model developed by OpenAI, enhances the conversational abilities of virtual agents, allowing for more nuanced and comprehensive interactions (Ramachandiran & Jomhari, 2018). Generative AI technologies enable the creation of new, diverse content, expanding the scope of virtual agent capabilities beyond mere conversation (May & Kirwan, 2013).

Sentiment analysis adds a layer of emotional intelligence, enabling virtual agents to detect and respond to the emotional states of users (Lee, Kavya, & Lasser, 2021). Lastly, computer vision technology equips agents with the ability to interpret visual data, further extending their applicability in various domains (Zojaji, Peters, & Pelachaud, 2020).

These technologies collectively enable virtual agents to understand user input accurately, generate appropriate responses, and continuously improve their performance through learning and adaptation, making them increasingly effective in a range of applications.

The integration of virtual agents within the service industry marks a pivotal shift towards digital transformation, enhancing the way services are delivered to consumers across various sectors, including hospitality, healthcare, retail, finance, and more. These virtual agents, powered by advanced technologies such as artificial intelligence (AI) and machine learning

(ML), are designed to simulate human-like interactions, offering personalized and efficient customer service around the clock.

Virtual agents present a cost-effective solution for businesses by automating routine tasks, such as answering frequently asked questions, booking appointments, and processing transactions, which traditionally require human intervention. This automation allows companies to handle a higher volume of customer interactions without the need for significant increases in staff, leading to considerable savings in labor costs. Moreover, virtual agents are not bound by physical or temporal limitations, providing customers with immediate assistance at any hour, thereby enhancing accessibility and responsiveness to customer needs.

The scalability of virtual agents is another critical advantage, enabling businesses to adjust their customer service capabilities based on demand. During peak times, virtual agents can effortlessly manage the increased workload, ensuring that customer service quality does not suffer due to high traffic volumes. This flexibility helps businesses avoid the pitfalls of understaffing or overstaffing, maintaining operational efficiency and customer satisfaction. Consistency in customer service is ensured through virtual agents, as they are programmed to deliver standardized responses based on best practices and company policies. This uniformity guarantees that all customers receive the same level of service and information, fostering trust and reliability in the brand. Furthermore, virtual agents are equipped with capabilities for hyper-personalization, analysing customer data to tailor recommendations, offers, and solutions specifically to individual needs. This level of personalization not only improves customer satisfaction but also enhances loyalty by making customers feel valued and understood.

Despite the numerous benefits, the adoption of virtual agents is not without its challenges. High initial investment costs for development and implementation can be a barrier, especially for small and medium-sized enterprises. Integrating virtual agents into existing systems and ensuring they work seamlessly with legacy technologies can also present difficulties, requiring time and resources to overcome. Data privacy and security concerns are paramount, as virtual agents often process sensitive customer information. Businesses must ensure robust security measures are in place to protect against breaches and maintain customer trust. Additionally, the effectiveness of virtual agents in handling complex or unpredictable queries can be limited, necessitating human intervention for resolution in some cases. Customer acceptance varies, with some customers preferring human interaction over dealing with a machine. Businesses must carefully design and implement their virtual agents to offer a user-friendly and satisfactory experience to overcome scepticism and resistance. The ongoing advancements in AI and natural language processing technologies continue to enhance the capabilities and effectiveness of virtual agents. As businesses become more familiar with the potential benefits and learn to navigate the challenges, the adoption of virtual agents in the service industry is expected to grow, driving innovation and improving the quality of customer service across the board. This digital shift not only offers operational efficiencies for businesses but also paves the way for a more personalized and accessible customer service experience.

### 1.2 Research Problem

The adoption of virtual agents, also known as chatbots or AI-powered virtual assistants, in the services sector has gained substantial attention in recent years. These digital entities have the potential to transform the way businesses interact with their customers, automate routine tasks, and improve overall service quality. However, while there is a growing interest in incorporating virtual agents into various service-oriented industries, there is a clear need for a more profound understanding of the motivations driving this adoption and the challenges organizations encounter during the implementation process.

The primary motivation behind the adoption of virtual agents in the services sector lies in the pursuit of improved efficiency, cost reduction, and enhanced customer experiences. Organizations aim to leverage these AI-powered tools to streamline their operations, reduce manual workloads, and provide quicker and more accessible customer support. By doing so, they seek to stay competitive in a rapidly evolving market and meet the growing expectations of consumers who increasingly prefer self-service and convenient interactions with businesses. These motivations underscore the importance of studying why organizations choose to invest in virtual agent technology.

Despite the promising advantages, the adoption of virtual agents in the services sector is not without its challenges. Organizations encounter a range of obstacles that hinder successful implementation. These challenges can include issues related to technology integration, data security concerns, customization to meet specific service requirements, and resistance from employees or customers. Moreover, there are ethical considerations concerning the use of AI in customer interactions, such as privacy and transparency. Understanding these challenges is crucial for devising strategies to overcome them and ensuring the successful integration of virtual agents into the services sector.

This study seeks to delve into these motivations and challenges comprehensively. By investigating the factors driving the adoption of virtual agents and identifying the hurdles organizations face during implementation, it aims to contribute valuable insights to both academia and industry. A deeper understanding of these issues can guide businesses in making informed decisions about the integration of virtual agents, ultimately helping them enhance their service delivery, improve customer satisfaction, and navigate the evolving landscape of the services sector in an increasingly digital world.

### 1.3 Research Purpose

The adoption of virtual agents in the services sector has emerged as a significant trend due to their potential to enhance customer service, operational efficiency, and overall productivity. However, despite their increasing prevalence, there exists a gap in understanding the motivations driving businesses to adopt these technologies and the challenges they encounter during the adoption process.

The motivations to adopt virtual agents could range from enhancing customer experience, improving service delivery speed, reducing cost, or gaining a competitive edge. Understanding these motivations can provide vital insights into how businesses perceive the benefits of virtual agents, and thus, can guide strategies for wider implementation and acceptance.

Concurrently, the challenges of adopting virtual agents in the services sector are complex and multi-faceted. They may encompass technical issues such as integration with existing systems, maintaining interaction quality, managing customer data privacy, and building user trust. Businesses may also face organizational challenges such as resistance to change, lack of skilled workforce, and high investment costs. These challenges can potentially deter or slow down the adoption of virtual agents, hence understanding them can help businesses to better navigate the implementation process and devise effective strategies to mitigate these challenges.

Furthermore, the interplay between the motivations and challenges is a significant aspect of this research problem. It is crucial to examine how these factors interact and influence the overall decision-making process regarding the adoption of virtual agents. For instance, how does the severity of the challenges impact the perceived benefits and thus influence the adoption decision?

The purpose of this research is to delve into an in-depth understanding of the motivations and challenges that are associated with the adoption of virtual agents in the services sector. The study seeks to identify and examine the key motivating factors that drive businesses to adopt virtual agents, the challenges they encounter in the process of adoption, and how these variables impact the overall adoption and implementation of virtual agents in the services sector.

### 1.4 Significance of the Study

The significance of the study on the motivations and challenges in the adoption of virtual agents in the services sector cannot be understated in today's rapidly evolving business landscape. This research holds several key implications and benefits for various stakeholders, including businesses, policymakers, technology providers, and consumers.

First and foremost, this study provides valuable insights for businesses operating in the services sector. Understanding the motivations driving the adoption of virtual agents allows organizations to make informed decisions about investing in this technology. By identifying the specific benefits, such as improved efficiency and enhanced customer experiences, businesses can strategize effectively to gain a competitive edge. Additionally, by comprehensively addressing the challenges associated with implementation, this research equips businesses with the knowledge needed to overcome obstacles and maximize the successful integration of virtual agents into their operations.

Policymakers and regulatory bodies also stand to benefit from this study. As AI and virtual agent technology continues to proliferate in various industries, policymakers must consider the implications of their usage. This research can inform the development of guidelines and regulations to ensure ethical and responsible deployment of virtual agents, especially concerning data privacy, security, and transparency. It can assist in creating a balanced regulatory framework that fosters innovation while safeguarding consumer interests.

Technology providers and developers in the AI industry can leverage the findings of this study to refine their offerings. Understanding the motivations behind adoption helps them tailor their products and services to meet the specific needs and expectations of businesses in the services sector. Moreover, by recognizing the challenges organizations face, technology providers can develop solutions and support mechanisms that address these issues, ultimately facilitating smoother and more successful implementations.

From a consumer perspective, the study's significance lies in its potential to improve the quality of interactions with businesses. By shedding light on the motivations behind virtual agent adoption, consumers can gain a better understanding of the benefits they can expect from these technologies. Additionally, addressing the challenges ensures that businesses take into account ethical considerations, data protection, and user-friendliness, leading to more trustworthy and satisfactory experiences for customers.

In summary, this study on the motivations and challenges in the adoption of virtual agents in the services sector has broad implications for businesses, policymakers, technology providers, and consumers alike. It has the potential to drive informed decision-making, responsible technology development, and enhanced customer experiences, contributing to the overall advancement of the services sector in an increasingly digital and AI-driven world.

## 1.5 Research Questions

1. What specific factors motivate the adoption of virtual agents in the services sector?
2. What are the particular challenges that the services sector encounters in the adoption of virtual agents?
3. How do the identified motivations influence the adoption of virtual agents in the services sector?
4. How do the identified challenges impact the adoption process of virtual agents in the services sector?
5. How do the motivations and challenges interact and what is their combined impact on the adoption of virtual agents in the services sector?

# Chapter II – Literature Review

## 2.1 Artificial Intelligence

The advent of artificial intelligence (AI) has brought about significant transformations in various sectors, with virtual agents being one of the most prominent manifestations of this technology. Virtual agents, also known as chatbots or AI agents, are computer programs designed to interact with humans in a natural, human-like manner (Lai, 2000). These agents have found applications in a wide range of sectors, including e-commerce (Antonescu, Barbu, & Luchian, 2017), education (Kazoun, Kokkinaki, & Chedrawi, 2022), healthcare (Kocakoç, 2022), and tourism (Antonescu et al., 2017), among others.

The interaction between humans and virtual agents has been a subject of extensive research in recent years, with scholars examining various aspects of this interaction, including the factors influencing the adoption of virtual agents, their impact on user experience, and strategies for improving their effectiveness (Contreras & Valette-Florence, 2023; Brachten, Kissmer, & Stieglitz, 2021; Justo et al., 2018). This literature review aims to provide a comprehensive overview of the current state of knowledge in this field.

Artificial intelligence (AI) systems are a collection of software and hardware components that may be used to continuously assess and analyze data in order to characterize environmental elements and make judgments and take actions (European Commission, 2018). Prior research has concentrated on the benefits of using AI in online settings but has neglected to examine how consumers accept AI in online shopping. According to utility theory, this new technology enables consumers to discover and select the best product alternatives while lowering the cost and duration of the search. The field of artificial intelligence (AI) has a much longer history than is commonly recognised, spanning fields as diverse as science and philosophy all the way back to ancient Greece (Collins, et al., 2021). However, its modern iteration owes a great deal to Alan Turing and a conference held at Dartmouth College in 1956 (McCorduck, 2004), where the term Artificial Intelligence was officially coined and defined by John McCarthy at the time the term the birth of artificial intelligence was used by Russell and Norvig (2020) to describe this event.

According to existing research, technological advancements in apps such as Artificial Intelligence (AI), Augmented Reality (AR), and Virtual Reality (VR) provide highly personalised experiences that influence consumer preferences and behaviours (Huang and Rust, 2017; Pantano and Pizzi, 2020). AR-enabled apps, for example, increase consumers' perceptions of utilitarian and hedonic benefits (Nikhashemi et al., 2021), promote positive attitudes (Yaoyuneyong et al., 2016; Wedel et al., 2020), and increase purchase intentions and word-of-mouth (Yaoyuneyong et al., 2016). Two separate studies published these findings (Rauschnabel et al., 2019). Similarly, virtual reality (VR) apps elicit a positive emotional response to the brand by eliciting powerful sensory responses, such as perceptions of tangibility through haptic vibrations (Wedel et al., 2020). Apps improve user interactions by providing a humanised customer experience, which influences how consumers perceive the brand associated with the app (Esch et al., 2019; Olson and Mourey, 2019), and increases trust regardless of privacy concerns (Alnawas and Aburub, 2016). This is accomplished by employing anthropomorphic cues, which are defined as human characteristics assigned to computers (Nass & Moon, 2000; Ha et al., 2020; and Esch et al., 2019). The global VR/AR app market is one of the fastest growing domains of software development (Unity Apps, 2021), but this line of research has not thoroughly evaluated the effects of app technological advancements on consumer experiences. Despite the fact that it is in line with current industry trends (the global VR/AR app market is one of the fastest growing domains of software development), it is possible that this knowledge gap is caused by outmoded theoretical foundations such as the diffusion of innovation (Rogers, 1995), the Uses and

Gratification (U&G) theory (Mcguire, 1974; Eighmey and McCord, 1998), and the Technology Continuance Theory (TCT) (Liao, Palvia and Chen, 2009). As a result, future research may include new theoretical approaches such as the physical and psychological continuity theory (Lacewing, 2010), the teletransportation theory (Langford and Ramachandran, 2013), and the service prototyping theory (Razek et al., 2018).

Vada et al. (2019) explored that some experiences are pleasant and unforgettable, whilst others are not so pleasant and memorable. Automatic messaging services (a type of artificial intelligence) used by service organizations such as hotels and airlines, for example, provide ease to customers who need assistance after business hours. However, this artificial intelligence tool allows for only a limited amount of customization of communications for unique clients, which may result in dissatisfaction with the service. Customers that have a high level of emotional intelligence may be more accepting of the services provided by artificial intelligence systems. Employee service, on the other hand, is not always a pleasant experience for the employees. Joshi, Chirputkar, & Jog (2015), believed that brand-oriented behavioural features and brand-focused attitudinal elements are particularly important in persuading buyers to stick with a particular brand. There are no prepaid mobile connections included in the study, therefore this is the only option. Customer happiness is one of the most essential factors in boosting the acquisition and retention of new consumers and is one of the most difficult to measure. Aside from that, the survey reveals that consumer satisfaction levels are influenced by a variety of factors such as brand choice, customer perception, distributor perception, marketing strategy, service quality, and delivery.

Balakrishnan et al. (2009) proposed using 'address mapping' to geo-locate IP addresses in order to find mobile phones. Address mapping can be used anywhere and is simple for business owners to implement at a low cost. Foursquare encountered some cases of the basic cheating method that worked in its early days as a real example of location cheating.

Foursquare has adopted the cheater code as a solution to defend against location cheating attacks, which verifies a device's location by using the GPS function of that device (Balakrishnan et al., 2009). Mobile device management (MDM) solutions (such as SOTI or Airwatch) are critical in the bring your own device (BYOD) model. These solutions create a sandbox in which enterprise apps can be stored and run. These solutions enable administrators to define compliance requirements, remotely wipe data, and manage the overall operation of the devices. Administrators can disable native apps, allow only trusted apps, implement remote device locking, and use other techniques. In general, all MDM solutions include data encryption, certificate support, and strong authentication measures as part of their mobile security strategy.

In today's competitive consumer market, it is critical for all service companies to maintain a high level of customer retention, and this topic will receive a lot of attention over the next few years (Appiah-Adu, 1999). This is because businesses regard consumers as a true asset, and the vast majority of them are experiencing significant losses in their consumer base (Swanson and Hsu, 2009). Because of the significant expansion, change, and increase in competition that has occurred in the mobile phone market on both a global and domestic scale, CR has emerged as a critical phenomenon in this industry. Despite using a variety of relationship marketing strategies (Gronroos, 1995; Ravald and Gronroos, 1996; Ranaweera and Prabhu, 2003), a sizable number of mobile phone companies are losing their current customer bases at rates greater than thirty per cent (Gronroos, 1995; Ravald and Gronroos, 1996; Ranaweera and Prabhu, 2003). Furthermore, Andic (2006) discovered that the major UK mobile network operators, such as Orange, T-Mobile, O2, and Vodafone, lose more than a third of their young customers to competitors. Customers under the age of 25 are included. While this is occurring, many managers are unable to confront that fact in the majority of situations, despite the fact that they are attempting to determine why they are experiencing such a loss (Reichheld, 1996). As a result, these mobile operators cannot afford to lose current and potential customers; a loss of this magnitude would result in lower sales and profits, which would eventually lead to business failure (Reichheld and Sasser, 1990; Reichheld and Kenny, 1990). In the cellular industry, there is a significant disparity between the rates of customer acquisition and customer retention. As a result of this disparity, the issue of customer retention has been approached from a variety of perspectives, including economic, behavioural, and psychological perspectives. The vast majority of previous studies were unsuccessful in providing a strong theoretical justification and practical explanation for the customer's repeat purchase from the standpoint of their behaviour.

According to Hall (2019), artificial intelligence marketing is the use of technology to improve the customer experience. Similarly, the intervention of information technology, particularly AI, has had an impact on the role of marketing managers. This is because it is now more important to better understand the customers or risk losing them to competitors who respond to their needs and desires. AI enables commercial enterprises to gain a better understanding of their customers and evaluate how those customers interact with the products and services they buy. When you have access to all of the necessary data about your intended customers, you can make more informed decisions about the company's direction.

Schrage and Kiron (2018) conducted a global executive study of strategic measurement and discovered that 79 per cent of CEOs who responded to their survey believe in investing in the skills and training of their marketing professionals to increase the effectiveness of machine learning (ML) in marketing. It is widely assumed that the rise of artificial intelligence in marketing, specifically CRM, will result in massive layoffs across the economy. This is due to the automation of tasks that were previously performed by humans but have since been replaced by machines (Schrage & Kiron, 2018). However, according to the United States Bureau of Labor Statistics (2020), the overall employment of advertising, promotions, and marketing managers is expected to grow by 6% from 2019 to 2029. Managers with digital marketing skills will have the best job prospects during this time period (US Bureau of Labor Statistics, 2020). It is also important to remember that artificial intelligence is a machine-based process, and it is widely assumed that AI is incapable of replicating human intuition and creative abilities (Jarrahi, 2018). However, it is more important to understand how marketing managers' roles are changing as the number of tools that automate and support marketing decisions grows (Dawar, 2020).

“In the early days of artificial intelligence, one of the dominant hypotheses was that it centred on high-level” cognition. “What distinguishes humans from most other animals is not the ability to” recognise concepts or perceive “objects to perform complex motor skills, but the ability to engage in multi-step reasoning, understand the meaning of natural language, design innovative artefacts, generate novel plans that achieve goals, and even the ability to reason about their own reasoning (Langley, 2011)”. Strong “AI was the term used to describe this broad human-like intellect (Kurzweil, 2005)”. “The fundamental approach to strong artificial intelligence has been centred on symbolic thinking, the idea being that” computers “are not only numeric calculators but rather generic” symbol manipulators. As emphasised “by Newell and Simon (1976) in their physical symbol system theory, the capacity to read and alter symbolic” structures seems “to be required for intelligent behaviour, according to their findings”. While this technique first seemed promising (Newell and Simon, 1963), several disciplines “of artificial intelligence have withdrawn from it as a result of its difficulties and lack of development as I enter the twenty-first century. It is still unclear when and whether powerful artificial intelligence will become a reality”.

Kaka et al. (2019) express that India is home to the greatest “number of publicly traded companies in the whole world. Because of the Indian Government’s Make in India digital technology” drive, “the country” now provides significant “growth chances to both domestic and foreign enterprises in terms of investment prospects and growth opportunities”, both domestic and international. Rural and “urban areas now have a more significant opportunity to increase per capita household income as” a result of this, which is encouraging news. The majority of customers, “who are likely to be from” "rural or urban regions with weak basic infrastructure or no access at all, are looking for lower costs, limitless phone and Internet service, and more value-added services." "Artificial intelligence, machine learning, deep learning, chat boxes, online shopping, online education, online games, and several more" advances were brought about by the digital revolution. “Telecommunications networks serve as the backbone that connects all of these digital technologies. As a result, telecommunications is playing an increasingly important role in advancing the country's economic development. Customers in metropolitan, city and metro areas want high-speed internet access for a variety of reasons, including” "audio-video streaming, navigation, music downloads, gaming, e-commerce, postal solutions, video chat boxes, and social networking." “Therefore, demand for 4G/5G technology to power these applications continues to grow incessantly. People who live in rural areas, as opposed to those who live in urban areas, require low-cost technology to use these applications. The government is carrying out various programs to make digital technology available, especially in rural and urban areas”. In addition, various programs, including digital technology," a 100 per cent foreign direct investment policy, the introduction of VNO licenses, “mobile number portability, special number service 112, Aadhar-based e KYC, GPS-enabled handsets, spectrum sharing, spectrum management, and spectrum auction”, have all contributed to the improvement of the health of the telecom sectors in the country." Airlines like Airtel and Reliance JIO have expressed an interest in connecting 10,000 villages, respectively, while Vodafone and Reliance JIO have expressed an interest in connecting 3000 and 1000 villages, respectively, among the companies that have expressed an interest in connecting 10,000 villages. There has been fierce competition among Indian telecommunications companies as a result of Reliance JIO's complementary offerings, which include limitless phone and data usage. Additional pressure is being exerted on telecom service providers such as Airtel, Vodafone Idea, and BSNL to cut their prices for acquiring and sustaining new and existing users. At the very least, Airtel, Vodafone Idea, and BSNL have acquired a foothold in what has become a fiercely competitive market as a result of Reliance JIO's entry into the telecom business.

Bedi and Surbhi (2017) pointed out that there are major obstacles, uncertainties, and a slew of concerns that must be addressed during the pre-merger and post-merger phases of a company's life cycle. Customers have become hesitant to purchase new services from the merged company as a result of the merger and acquisition, hence supporting the competition's competitor in growing its client base. It looks into the dynamics of trust following mergers and acquisitions, “as well as integration planning in the Indian telecom sector, as aspects that are responsible for a successful merger and its positive impact on customers, the market, and the company. Moreover, these variables are to blame for the negative outcomes of the” business's unfortunate merger with another organisation. According to Azam, Qiang, and Abdullah (2012), "”consumer happiness is not only a critical performance outcome in internet retail purchasing, but it is also a significant predictor of customer online shopping and purchase intention”. Among the criteria identified by the authors as having an impact on customers' willingness to make online purchases are customer happiness with the system, “service interfaces, security, currency relevancy, consistency, understandability, navigability, and telepresence”. Mobile number portability, according to Premkumar and Rajan (2012), are one of the most critical “factors in customer retention in the Indian mobile telecommunications market”, and it is a significant setback for mobile telecommunications service providers in the country. Further, “the results of the study showed customer satisfaction” is extremely important in terms of client retention. Customer retention “in the

Indian mobile" telecommunications "market is" inversely proportional to the level of customer satisfaction. Consumer happiness, on the other hand, is influenced by two characteristics: consumer trust and service excellence.

Artificial intelligence has the potential to impact revenue by a trillion dollars or more in the coming decade. It is having a significant impact on a wide range of business processes across multiple industries, causing widespread disruption. Never before have so many businesses invested in or planned to invest in artificial intelligence technology. There has also been a lot of interest from regular investors and venture capitalists. However, artificial intelligence remains "a complex technology involving numerous sub-concepts and intricate algorithms. There are also serious ethical concerns about" the use of AI. On the market today, there are numerous perspectives on artificial intelligence (AI). Makridakis (2017) classified these points of view into four groups: optimists, pessimists, pragmatists, and sceptics. "If managers and stakeholders know little about this new phenomenon" but are forced to make a decision due to market buzz and competitive pressures, then confused signals may trigger herding behaviour. Herding behaviour becomes especially intense "when there is no obvious path into the future and a general level of uncertainty in the market". Companies that are still evaluating the situation and unsure of what course of action to take in this scenario typically receive information from early adopters and use it in their decision-making processes "(Khanna & Mathews, 2011). Herding is especially common in the information technology sector, where managers are known to blindly follow one another in making IT investment decisions (Kauffman & Li, 2003)". Even if "not all herding" has a negative impact on the industry as a whole, it may have an impact on the expectations of a potentially useful technology within a single company. "A substantial amount of research has been conducted" on both manager herding and investor herding, particularly in the field of finance. Despite the fact that "fewer studies have investigated IT adoption herding, which results from corporate decision makers' investment decisions (Duan et al., 2005), many studies have" investigated the perspectives of "digital marketing and other online solutions. For example, it was discovered that" if there was a general trend of people in the digital world leaving negative comments, the effects of herding could be reduced (Huang & Chen, 2006). There is also a herding behaviour among lenders (investors) in the online loan market (Herzenstein et al., 2011).

Ding and Li (2019) discovered that both the consumption of digital books and the making of website purchases displayed significant signs of herding behaviour. Similarly, new bidders on eBay typically "flock to existing bids (Simonsohn & Ariely, 2008). To the best of the author's knowledge, no studies" have been conducted that combine AI and herding behaviour. In order "to promote the effective use of AI, it was necessary to measure the impact of any herding phenomenon on AI technology, analyse what factors triggered the herding, and determine the effects on the overall AI industry". This was done to determine what factors caused the herding.

The difficulties that must be overcome in order to implement "autonomous customer experience management were outlined by Gacanin and Wagner (2019). (CEM). The paper also included a narrative describing how AI and machine learning were used to create a" critical business value driver as well as an intelligence network. A chatbot "powered by artificial intelligence (AI) and equipped with natural language processing (NLP)" aided in improving the overall "customer experience (Nguyen and Sidorova, 2018)". The efficient "data processing made possible by AI and ML algorithms allows us to make the best decision (Maxwell et al., 2011)". The use "of AI is required in order to" analyse customer routines, purchases, preferences, and the like "(Chatterjee et al., 2019). Customer Relationship Management (CRM) functions" have been shown to benefit from "Artificial Intelligence User Interface (AIUI) functions (Seranmadevi & Kumar, 2019). Conventional retail establishments were transformed into smart retail establishments through the use of AI and IoT. The smart retail stores improved the customer experience, as well as" the convenience of shopping, and strengthened the supply chain. The authors Sha and Rajeswari (2019) discussed recent advances in artificial intelligence and demonstrated a machine powered by "AI that can monitor all five of a human's senses: sight, hearing, taste, smell, and touch. In the e-commerce sector, the findings indicated a stronger association between consumers and brands, as well as between products and brands".

"Promotion management includes media planning, media scheduling, advertising campaign management, search engine" optimization management, "and other" tasks. "Traditional methods of promotion are giving way to digital and physical ones". "Digital marketing and social media campaigns made significant progress as a result of the global digital" transformation. The consumer dictates "the content, location, and timing of an event in today's" rapidly evolving "technological" landscape. "AI enables message personalization and customization based on individual customers' preferences and profiles (Huang & Rust, 2020)". Using "content analytics can assist in increasing the value and effectiveness of messages. Emotional AI algorithms" enable real-time monitoring of individual customers' likes and dislikes. The use of netnography to analyse the content of social media platforms offers marketers new opportunities to align their marketing strategies with their customers' preferences (Tripathi & Verma, 2018).

Gray (2018) explored the other side of the AI system and wrote an article entitled "AI can be a troublesome teammate". He talks about an incident in his college time when he worked for an environmental surveying company, according to him it's the inability to feel of AI system that makes him untrustworthy. He believes that to trust their team members there are three things that are required first is mutual concern second is "a shared sense of vulnerability and faith in competence". The third element that makes AI untrustworthy is its biggest power that is its strength its superhuman ability to predict or calculate it become against AI when it is forced to work outside its limits but he does not totally deny the use of AI he says in some ways it has proven to be useful also lie in weather forecasting he too believes the AI function (Wirtz et al., 2018).

"Whang, Ren, and Lu (2018) explored the use of AI in telecommunication and led research entitled Key technologies of AI in customer service systems, Telecommunication Science they believed they artificial intelligence systems have some factors like very high efficiency and low expense when it is compared to traditional customer service operated by a human in the area of customer service in the business field". But it was told that current AI technology has some weaknesses too. For example, it was not flexible and its tone was very rigid and they too lack caring eventually "there is a high amount of automation on the organisation side, but there has been no increase" in the rate of succession and an exponential decrease in user experience was recorded on the side of customers. "Client satisfaction, according to Ra'ed (2012), has a positive impact on long-term customer retention. Further, Ra'ed (2012) found that there is a direct correlation between customer pleasure and the length of the supplier-customer relationship, that mobile services provided by call centres have an impact on customer satisfaction and retention". As a result of the study, it was discovered that there is fierce competition among Indian telecom providers, with all of them offering a variety of deals and programmes to maximize user base dependent on market conditions. Because of the competition, the author also encourages telecom players to match their operations with a new and dynamic business environment.

"In e-commerce contexts, interacting with clients using live chat interfaces has grown in popularity as a way to offer real-time customer assistance. Customers utilise these chat services to get assistance or information (such as product specifications) (e.g., solving technical problems). With the real-time nature of chat services, customer support has become a two-way conversation with major effects on WOM intentions, trust, satisfaction, and repurchase (Mero, 2018). Chat services have evolved into the main method for obtaining customer help during the past ten years (Charlton, 2013). Human chat service representatives have increasingly been supplanted by conversational software agents (CAs), such as chatbots, in recent years, thanks to advancements in artificial intelligence (AI) technology (Gnewuch et al., 2017; Pavlikova et al., 2003; Pfeuffer et al., 2019a)". Although primitive "CAs first appeared in the 1960s (Weizenbaum, 1966), the" "second wave of artificial intelligence" "(Launchbury, 2018) has reignited interest in and enhanced the dedication to this technology since it has opened the door for systems that can interact with humans more like humans (Gnewuch et al., 2017; Maedche et al., 2019; Pfeuffer et al., 2019b). Customers continue to have unpleasant experiences with AI-based CAs, despite technical advancements. For instance, CAs could respond to user requests inappropriately, causing a discrepancy. between what the user expects and how well the system performs" (Luger and Sellen, 2016; Orlowski, 2017). "Live chat services are being replaced by AI-based CAs, raising the question of whether they will remain useful given that scepticism and resistance to the technology may prevent task completion and hinder positive customer experiences. As a result, using these systems could push customers to engage in undesirable behaviours like noncompliance, which could be detrimental to both users and service providers" (Bowman et al., 2004). "However, the purpose of this self-service technology is called into question if users decide not to follow or adapt to the recommendations and requests made by the Cas" (Cialdini and Goldstein, 2004).

According to earlier research, "CAs should be anthropomorphically (i.e., human-like)" built in order to foster "a sense of social presence (Rafaeli and Noy, 2005; Derrick et al., 2011; Zhang et al., 2012; and Elkins et al. 2012)". "The majority of this research concentrated on the effects of" anthropomorphic design signals on human perceptions and adoptions “(Hess et al., 2009; Qiu and Benbasat, 2009; and Adam et al., 2019;)”. “This study offers important contributions to research and practice, but it has mostly concentrated on embodied CAs, which can apply nonverbal anthropomorphic design cues since they have a virtual body or face (i.e., facial expressions or physical appearance). However, chatbots are disembodied CAs that engage with users primarily through linguistic signals (Araujo, 2018; Feine et al., 2019). Although there has been some prior research on vocal anthropomorphic design signals, such as self-disclosure, excuse, and thanks (Feine et al., 2019), these cues have frequently been very static and insensitive to the user's input due to the older generations of CAs' poor capabilities. Users may grow resistant to such a system as a result since it cannot accurately simulate human-human conversation. Today, advanced chatbot solutions that carefully understand user input based on limited AI are made possible by conversational computing platforms (like IBM Watson Assistant). In comparison to the somewhat static responses of their rule-based predecessors, chatbots built on these systems are more flexible and compassionate and have comprehension that is closer to that of humans (Reeves and Nass, 1996). Thus, these platforms provide new anthropomorphic design cues like showing empathy through conversation. With a few notable exceptions (Araujo, 2018 and Derrick et al., 2011), the ramifications of more sophisticated anthropomorphic design cues have not been thoroughly investigated”.

“The question of whether compliance and persuasion techniques—which aim to persuade users to comply with or adapt to a certain request—are equally valid in these new technology-based self-service contexts also emerges as chatbots continue to replace human customer support representatives. The continued-question method is a type of foot-in-the-door compliance technique that is particularly pertinent since it is not just widely employed in practice but also because it has been demonstrated that the type of requester has a significant impact on the procedure's success” (Burger, 1999).

Finding “a balance between service efficiency and service quality is a major difficulty for customer service providers: The potential benefits of consumer self-service”, including increased “time efficiency, decreased costs, and improved customer experience, are emphasised by both researchers and practitioners (Meuter et al., 2005; Scherer et al., 2015). As a self-service technology, CAs promise to boost service quality and enhance provider-customer interactions while also providing a number of cost-saving opportunities (Gnewuch et al., 2017; Pavlikova et al., 2003). According to studies, CAs can cut down on response times, free up agents for other tasks, and handle up to 80% of routine enquiries, resulting in a 30% reduction in the $1.3 trillion in annual global company expenditures associated with 265 billion customer support requests (Reddy, 2017b; Techlabs, 2017). By 2022, businesses alone plan to save more than $8 billion annually on customer-supporting expenses, a significant rise from the $20 million in estimated savings for 2017. (Reddy, 2017a). Thus, CAs offer to be quick, easy, and affordable customer support options via electronic channels available around-the-clock (e.g., Hopkins and Silverman, 2016; Meuter et al., 2005)”.

“Customers typically value individualised attention in addition to easily available and adaptable self-service channels. As a result, businesses shouldn't totally switch to consumer self-service channels, especially at the start of a relationship with a client (Scherer et al., 2015), as the lack of a social intermediary in online transactions may result in a loss of sales (Raymond, 2001)”. However, by imitating social actors, CAs have the ability to “actively shape service encounters and to stand in for service workers by carrying out tasks that were previously handled by human service staff (e.g., Larivière et al., 2017; Verhagen et al., 2014). Customers can resort to CAs that are available 24/7 as an alternative to phoning a call centre or sending an email to ask a question or make a complaint. As the interface between” businesses and customers "gradually evolves to become technology dominant (i.e., intelligent assistants acting as a service interface) rather than human-driven (i.e., service employee acting as service interface)" "(Larivière et al., 2017, p. 239), this self-service channel will become more and more important. Recent AI-based CAs also include the option to flag human traits like friendliness, which are important for handling service interactions (Verhagen et al., 2014)". Therefore, by invoking notions of social presence and personalization in contrast to prior "online service interactions, CAs can lessen the prior absence of interpersonal engagement".

CAs, and chatbots in particular, are becoming a common sight "in online commerce and customer support on numerous websites, social media networks, and messaging apps". For instance, "between June 2016 and April 2019, the number of chatbots on Facebook Messenger increased from 11,000 to 300,000. (Facebook, 2019)". Although these technological artefacts are becoming more prevalent, earlier research suggested that chatbots "still have issues related to their infancy, leading to significant failure rates and user distrust when it comes to the employment of AI-based" chatbots (Orlowski, 2017). Furthermore, prior "studies have shown that while human language abilities easily translate to human-chatbot communication, there are noticeable disparities in the nature and calibre of such exchanges. For instance, people use more profanity and lengthier conversations with chatbots than they do with humans (Hill et al., 2015). As a result, if users treat chatbots differently, their cooperation in response to the chatbot's suggestions and requests may suffer. Thus, the merits of the self-service technology may be called into doubt. Therefore, it's critical to comprehend how chatbot design affects user compliance".

"The well-known social response theory (Nass et al., 1994) set the path for several research showing how people use anthropomorphically constructed computers to impose social standards. We define anthropomorphism, which is consistent with prior research in digital contexts, as the imputing of human-like traits, behaviours, and emotions to nonhuman actors (Epley et al., 2007). The phenomena can be explained as a natural human desire to apply anthropocentric information to make it easier to understand unknown actors (e.g., Epley et al., 2007; Pfeuffer et al., 2019a)".

"Human-computer interactions (HCIs) are fundamentally social, according to the social response theory (Nass and Moon, 2000; Nass et al., 1994). People are predisposed to automatically as well as unconsciously perceiving computers as social actors, even when they are aware that machines do not have feelings or intentions. The evolutionary-biased social orientation of humans is the identified psychological effect behind the "computers as social actors" (CASA) hypothesis (Nass and Moon, 2000; Reeves and Nass, 1996). The degree of salience of the other person in the interaction, which was originally a concept to gauge users' perceptions of human contact (i.e., warmth, empathy, and sociability) in technology-mediated interactions with other users, may therefore be perceived by a user through interacting with an anthropomorphized computer system (Qiu and Benbasat, 2009). Consequently, the term "agent," for instance, which originally denoted a human being who provides direction, has come to be used to refer to anthropomorphically constructed computer-based interfaces (Benlian et al., 2019; Qiu and Benbasat, 2009)".

"In HCI environments, people" react by engaging in social behaviour and attributing anthropomorphic qualities to technology that contains signs that are typically associated with human behaviour "(e.g., language, turn-taking, and interactivity) (Epley et al., 2007; Moon and Nass, 1996; Nass et al., 1995)". Individuals therefore treat computers and people according to the same social norms: Even a small number of "anthropomorphic design cues (ADCs) can cause social orientation and a sense of social presence in" a user during computer interactions, leading to reactions that are in accordance with socially desirable conduct. HCI follows the same social dynamics and principles that govern human-human interaction. "Nass et al. (1999), gender and racial stereotypes (Nass and Moon, 2000) personality response (Nass et al., 995), and flattery effects (Fogg and Nass, 1997)" are just a few examples of stereotypes that have been found in HCI through CASA studies.

Verbal ADCs, like the ability to talk, try to create the impression "of intelligence in a non-human technological agent as opposed to nonverbal ADCs, such physical appearance or embodiment", which strengthen "social connection by adopting motoric and static human traits (Eyssel et al., 2010; Araujo, 2018). As a result, static and motoric anthropomorphic embodiments through avatars" have been discovered to be primarily useful in marketing contexts "to influence trust and social bonding with virtual agents (Qiu and Benbasat, 2009), and particularly important for service encounters and online sales, for example on company websites (Etemad-Sajadi, 2016; Holzwarth et al., 2006), in virtual worlds (Jin, 2009;" Bertacchini et al., 2017). Although chatbots allow for "real-time dialogue through primarily text input, they lack physical and dynamic representations, with the exception of the typically static profile picture". Instead, "they interact with customers via messaging-based interfaces using verbal (e.g., language style) and nonverbal cues (e.g., blinking dots)". As a result, chatbots are essentially disembodied CAs. "To the best of our knowledge, no other studies have specifically addressed verbal ADCs" to further the body of information on embodied agents, with the exception of two outliers "that focused on verbal ADCs (Araujo, 2018; Go and Sundar, 2019)".

"The definition of compliance is" "a certain form of response, or acquiescence, to a specific kind of message, such as a request" "(Cialdini and Goldstein, 2004, p. 592)". "A door-to-door campaign asking for donations is an example of an explicit request. Alternatively, an implicit request can appear in a political advertisement endorsing a candidate without specifically urging voters to cast a ballot. However, in every instance, the targeted person is aware that they are being spoken to and asked to act in a particular way". Numerous compliance techniques, "including the that's-not-all technique (Burger, 1986), the disrupt-then-reframe technique (Davis and Knowles, 1999; Knowles and Linn, 2004), the door-in-the-face technique (Cialdini et al., 1975), and the foot-in-the-door (FITD)", have been the focus of compliance research (Burger, 1999).

In order to persuade people to comply, the FITD compliance strategy "(Burger, 1999; Freedman and Fraser, 1966) builds on the impact of tiny promises". In Freedman and Fraser's (1966) experiment, the FITD was first empirically tested by calling housewives and asking them "to answer a few questions about the home products they used. Three days later, the psychologists" contacted once more and requested permission "to send researchers to the home to go through cabinets as part of a 2-hour inventory of household items". When compared to "a group of housewives who simply received the large request", the researchers discovered that these ladies were twice as likely to comply. This compliance strategy is often used in modern online marketing and sales to get customers to make bigger commitments. For instance, websites frequently require visitors to make minor commitments "(such as submitting an email address, clicking a link, or sharing on social media), only to follow up with a larger request that is geared toward increasing conversions (e.g., asking for sale, software download, or credit-card information)".

"Individuals in compliance" circumstances must quickly comprehend, assess, and reply to a request (Cialdini, 2009). "As a result, they don't have time to completely consider all of their options and" instead rely on heuristics, or "rules of thumb," to assess their options (Simon, 1990). Small requests, as opposed to large ones, are more effective at persuading "subjects to agree with the requester because they require less mental work on the part of the subject". When people accept "a commitment, they are more likely to accept a bigger commitment" in the future to maintain their original behaviour. The FITD technique thus takes advantage of people's inclination to defend their initial acceptance of a tiny request to others and themselves.

The demand for consistency in conduct among people is based on a number of underlying psychological processes, the majority of which are based “on self-perception theory (Bem, 1972) and commitment-consistency theory (Burger, 1999). (Cialdini, 2001). These views suggest that people only have mediocre attitudes at birth and instead develop their attitudes through self-observation”. Therefore, if people agree to “an initial request, a bias develops and” they believe they must have found the request acceptable. As a result, they “are more likely to agree to an associated future request of the same kind or for the same reason (Kressmann et al., 2006)”. Indeed, prior marketing “research has actually shown that consumer need for self-consistency promotes purchasing behaviour (e.g., Ericksen and Sirgy, 1989)”.

Consistency has been shown to be a key element in social exchange in earlier studies. People tend to respond positively to requests in order to build relationships, and the stronger the relationship becomes, the more likely they are to comply “(Cialdini and Trost, 1998). In fact, even brief exposure to a person without any” contact greatly boosts adherence to “the person's request; this effect is even more pronounced when the request is” delivered in person and without warning “(Burger et al., 2001). In private contexts, people may even choose to comply with a request only to lessen feelings of guilt and” sympathy and to win others' favour in order to boost their self-esteem (Whatley et al., 1999). (Deutsch and Gerard, 1955).

Hao (2020) explored the side of call centres and led research which was “entitled “the pandemic is emptying call centres. AI chatbots are swooping in” “According to Hao, the world is currently facing an unprecedented COVID-19 pandemic, in which government entities and business organisations have reduced significantly staffing levels, while a significant chunk of the population locked up at home has significantly increased the number of voices calls for various online counselling sessions. As the epidemic spreads, understaffed government organisations, grocery shops, and financial institutions scramble to create artificially intelligent customer service systems to manage the increased volume of calls. The number of visitors to IBM's Watson Assistant jumped by 40% from February to April 2020. Despite the fact that contact centres have always been at the vanguard of workplace automation, the epidemic has significantly hastened the process. Organizations that are under stress are more inclined to test new tools and solutions to aid in the relevant business. According to Mehta (2013), the socioeconomic ramifications of mobile phone use in rural India are being investigated. Users' ability to obtain information for agricultural and non-agricultural purposes, as well as communicate with family members and migrant workers, was also revealed by the survey, which was conducted in late 2012. In rural India, the demographic characteristics of mobile phone users (ownership and access), their usage (social and economic), their activity (education, entertainment, and inventive use), and their impact (satisfaction, safety, skills, and income) are all important considerations to consider.

Schrotenboer (2019) reviewed the topic entitled “the impact of artificial intelligence along the customer journey” he said Online businesses may employ artificial intelligence to improve client experience and help them adapt to socialisation.' However, artificial intelligence has an impact on how people purchase in physical shops, and as a result, the gap between offline (brick-and-mortar) and online shopping is narrowing (e-commerce). AI technology can improve this user experience, therefore marketers need to understand how well these advancements affect the consumer experiences in an ever world. This thesis presents a framework for businesses and other scholars to understand how recommendation systems and conversational interfaces may help firms improve the customer experience across the customer journey while emphasising the significance of fully understanding consumer behaviour.

Bowen and Morsan (2018) in their research which was entitled “Beware hospitality industry: the robots are coming. Worldwide Hospitality and Tourism Themes” provide an outline of how artificial intelligence and robotics are used in the service industry According to their research, AI can extract the actual value of the massive amounts of consumer data accessible, which can then be leveraged to enhance customer experience by providing more personalised services. Auto-cars (a sort of AI) may, for example, pick up clients from the airport, assist them in checking into a hotel, and set up a customer's smartphone to serve as a key. The AI-driven automobiles can recommend eateries near hotels and make reservations for customers based on their preferences.

Salovey and Mayer (1990) explored emotional intelligence in a paper entitled as “emotional intelligence”. Individuals' emotional talents to recognise, comprehend, use, and control their own and others' emotions are referred to as emotional intelligence is divided into four categories: emotional observation, emotional absorption, emotional comprehension, and emotion management. Each brand stands for a particular set of emotional capabilities (Prentice, 2019). These qualities allow someone who is emotionally intelligent to comprehend and empathise with others. Consumers' emotional maturity may assist them to connect with workers on an emotional level to improve their experience with employee service in the event of a service contact.

Prentice, Chen, & King (2013) studied how emotional intelligence and occupational commitment have a moderating effect on the relationship between labour’s emotion and their potential outcome in research entitled “Employee performance outcomes and burnout following the presentation-of-self in customer-service contexts” Customers' engagement and loyalty are highly influenced by their total experience with both workers and AI, according to the research. None of the AI dimensions is substantially connected to customer engagement when all sub-dimensions of staff and AI service are regressed. Employee responsiveness, empathy, and assurance, on the other hand, have a considerable impact on the outcome variable. Employee responsiveness refers to the speed with which services are delivered, as well as the desire of workers to assist clients and their availability to answer to their demands. In the context of AI services, responsiveness refers to how quickly the AI technologies respond. Although AI-powered technologies may answer quickly, in most circumstances, the solutions provided by robots are standardised. Customers, on the other hand, enjoy dealing with staff and report having a better experience as a consequence of employee answers. Finally, they present a planned model that helps institutes think about the internal and external implications of AI, which they label the Three C Model of Confidence, Change, and Control.

Pavaloiu (2016) wrote a paper entitled "The Impact of Artificial Intelligence on Global Trends. Journal of Multidisciplinary Developments" in which she investigates how artificial intelligence influences worldwide trends and how it provides a viewpoint on how to change the external stimuli, marketing techniques and management which is affecting the consumers and altering their attitude towards business.

Smidt and Power (2020) asserted that internet product research has expanded dramatically in recent years. Amazon, the largest online retailer in the United States, is a shining example of how to integrate AI efficiently into online retail. Apart from the extensive selection, quick delivery, and low pricing, a more tailored shopping journey may be developed. Thus, Amazon may offer location-specific pricing and communicate with customers in their native currency (Barmada, 2020).

Novel marketing strategies, aided by new technology, such as the usage of artificial intelligence (AI) systems, stimulate the development of new marketing methods for effectively reaching target consumers and providing superior consumer experiences (Pusztahelyi, 2020). AI enables customer-centric search and a new level of personalization in online purchasing, resulting in a more efficient sales process. The nature of business-customer connections has shifted as a result of information technology (IT) (Rust and Huang, 2014). However, every transformation powered by technology is predicated on trust (Pricewaterhouse, 2018).

The chatbot begins by analyzing the primary fundamental concepts and then delves further into the subject. If the user initiates the discussion with a query, the chatbot attempts to evaluate the primary subject first and then uses the funnel concept to further reduce the subject (Dempt, 2016). By using regular and data-driven semantic methods, the software attempts to interpret the user's content. Automatic recognition of data expressions is the goal of rule-based approaches. Data-driven methodologies operate similarly to qualitative social research's content analysis. Deductive categories are constructed in advance, and then use words are coded using these categories to swiftly assign them to related topics (Trendone, 2016).

Humans have a greater level of trust in a chatbot when it is viewed as a team member rather than a technological gadget. When bots appear in a partnership-oriented manner and communicate in a manner similar to that of their users, information is deemed more reliable (Reeves & Nass, 1996).

People have certain expectations of computers and software such as chatbots. That is, consumers do not expect their responses to be bullet-pointed and do not wish to be overburdened with information. Ideally, the chatbot should reflect the essential information precisely and politely. To accomplish this, it is critical that the chatbot recognizes and learns about the returning user over time, based on previous discussions and search requests (Reeves & Nass, 1996). To improve customer service efficiency and to meet customers where they are, service providers offer customer care via a variety of online channels, including company websites, social media, email, and chat. Customer support via chat is becoming increasingly important. Chat is a more resource-efficient method for the service provider than email or telephone help, as customer service representatives may handle several queries concurrently (Tezcan & Zhang, 2014).

### 2.2 Customer Experience with Artificial Intelligence

Pretince and Nguyen (2020) explored the distinct method for engaging customers by using artificial intelligence in a paper which was entitled “engaging and retaining customers with AI and employee service”. The method used by them for carrying out this research was by a poll performed with customers who have used AI products and services in Australia, with an emphasis on hotels. Chatbots, conversational robots, virtual help, voice-activated services, and enhancers of travel experiences are among the AI tools used by the selected hotels in order to provide services to customers. Qualtrics was used to recruit the target respondents since it has user-friendly facilities for participants. Potential participants must be over 18 for this study they should also have stayed at one of the Australian hotels that have used artificial intelligence tools within the last three months of the study. These requirements were addressed by screening queries. For this investigation, digital snowball sampling was used. Artificial intelligence (AI) is increasingly being used in service companies to operate effectively and efficiently and client experience. The findings of this research concluded and showed them how Customers' engagement and loyalty are highly influenced by their total experience with both employees and AI, according to the findings. Neither of the Intelligence dimensions is significantly connected to customer engagement when all sub-dimensions of staff and AI service are regressed.

Customers who are informed about the advantages of doing business with a particular company are more likely to do so. It is not always a pleasant experience to interact with the service staff of the company and the AI services because employees may be affected by moods and emotions, which influence their attitudes and behaviors when interacting with customers. This can make dealing with the service staff and AI services of the company difficult (Prentice, 2013). Employees in service roles interact with both internal coworkers and management as well as external customers on a regular basis because of the boundary roles they play in the organisation. As a result of role conflicts and a lack of support from management, employee service performance and, as a direct consequence of this, customer experience and perception can be negatively impacted (Neves and Eisenberger, 2012). From the point of view of the customer, on the other hand, the potential costs of switching and the perceived benefits may be enough to motivate them to look for ways to improve their experience and engagement with the organisation. They may be able to expand the tolerance zones of customers and empathise with personnel in order to convince them to accept a lower level of service because of their high level of emotional intelligence.

Consumer loyalty indicates that a customer will continue to use a product or products offered by the same company, make referrals to other businesses, and either intentionally or unintentionally provide strong word-of-mouth references and publicity (Bowen and Shoemaker, 1998). Oliver (1999) defines loyalty as "a deeply held psychological commitment to consistently repurchase or re-patronize a preferred product/service in the future, resulting in the repetitive same brand or same brand-set purchasing, despite situational influences and marketing efforts having the potential to cause switching behavior." In other words, loyalty is "a deeply held psychological commitment to consistently repurchase or repatronize a preferred product/service in the future, resulting in repetitive same brand or same brand-set purchasing." The authors Javalgi and Moberg (1997) defined loyalty from three different perspectives: behavioural, attitudinal, and decision-making. The attitudinal perspective takes into account a customer's preferences in addition to their feelings about a particular brand, in contrast to the behavioural perspective, which is based on the number of times a specific brand was purchased.

Mobile marketing is viewed as a potential investment area as well as a way to improve the level of satisfaction experienced by customers. It also helps to strengthen the relationship between the parties and contributes to an increase in consumer communication and interaction between customers and businesses, which ultimately results in an increase in customer satisfaction and loyalty (Anjorin and Amarsana, 2012). Mobile marketing is one of the active forces that can have an effect on a company's brand awareness, composition, and loyalty (Galeano et al., 2016). The internal promotion has a direct impact on impulsive purchases made online, whereas external promotion has an indirect impact through its ability to elicit positive responses to online in-store promotion (Bucht and Gillberg, 2015).

Mohannad, Daqar, & Smoudy (2019) conducted research entitled “The Role of Artificial Intelligence on Enhancing Customer Experience”, which aims to look into the function of artificial intelligence (AI) in enhancing the customer experience in several businesses in Palestine, such as banks and telecommunication providers. The primary data for this study came from interviews and a standardised questionnaire. The study's findings demonstrated that AI and customer experience had a good and significant association. AI accounted for 26.4 per cent of the variance in customer satisfaction ($R2=0.264$, $F(1.89)=28.634$, $P$ 0.05). Customer experience has two dimensions: customer service and after-sale support. According to the study, AI predicted 22.9 per cent of customer service variance, but only 7% of after-sale support variance. Furthermore, delivering Personalized Customer Service throughout a customer's purchasing journey has a significant impact on customer satisfaction. According to the report, businesses should provide more individualized services to clients, since this has an impact on their overall experience with the company. Similarly, using AI in call centres and other after-sales support services to reduce client wait times is highly encouraged. In order to explore how organizations gain from deploying AI, a sample of two companies was selected and interviewed for the qualitative method. Because the quantitative approach's population comprises all Internet users in Palestine, a random sample of this large population was chosen. The questionnaire was then filled out by a random sample of 80-90 users in order to examine their attitudes regarding AI. The authors find that the research hypotheses fit their results after comparing the outcomes of the executed analysis. First, the regression and correlation studies show that there is still a favorable association between AI and user experience, as well as a direct link between AI and offering tailored customer care including after-customer assistance. Authors demonstrate that delivering individualised customer care throughout the client's purchase journey has a significant influence on the customer experience by combining descriptive analysis with the previous findings. Additionally, using AI in contact centres and other after-sales support services would reduce client wait times, hence improving the customer experience.

Yau, Saad and Chong (2021) led a research entitled “Artificial Intelligence Marketing (AIM) for Enhancing Customer Relationships they presented an artificial intelligence marketing (AIM) framework based on the literature that allows automated systems to obtain big information and data, utilise AI technology to generate knowledge, and afterwards distribute and implement that knowledge and improve relationships with customers in an experience and understanding environment. They pulled together and curate a broad variety of relevant literature, including real-life instances and cases, to construct the AIM framework, and then they analyse how these literature contribute to the framework in the study subject. They discussed the AIM framework from an interdisciplinary standpoint, emphasising the importance of artificial intelligence and marketing research in academia. Pre-processor, main processor, and memory storage are the three essential components of the AIM framework. The essential component, the main processor, employs artificial intelligence to interpret structured data processed by the pre-processor in order to make real-time judgments and reasonings. The artificial intelligence method is distinguished by its hypothetical powers, learning paradigms, and human-like operating modes. The strategic use of the literature-based AIM framework to improve customer relationships is discussed, including customer trust, satisfaction, commitment, engagement, and loyalty. Finally, prospective research avenues are discussed in order to further this multidisciplinary study area. The conclusion that they derived was based on the aim framework they considered that this provided them four considerable advantages including increasing the efficiency of activities in the marketing sector also increasing the accuracy of decisions made in solving problems and predictions that are made in reasoning based on big data. They finally concluded that Artificial intelligence marketing (AIM), an interdisciplinary study area, is a disruptive technology that allows computers to automate the process of gathering and analyzing large amounts of data and information in order to develop marketing mix expertise. This skill is required to provide scaled personalisation, which has hitherto proven difficult to do with human effort alone. This study reviews the research and proposes an AIM framework for improving customer relationships, encompassing consumer trust, contentment, dedication, involvement, and commitment. The strategic framework is made up of three primary components: a pre-processor, the main processor, and memory storage, and it was created using a variety of relevant literature. The primary processor's putative powers, learning paradigms, and human operating modes may all be used to describe it. Despite the proposed AIM framework's completeness, there are various research possibilities, such as (a) learning sentimentality or mindset; (b) removing discrimination and prejudice; (c) improving interpretability and understandability; (d) having to learn tacit and explicit knowledge; and (e) explore different ability to obtain and harness consumer, user, and outer market information.

Berry et al. (2006) discovered that AI-powered services are classified as functional experiences in their study of service experience typology. Nanji (2019) states that the vast majority of users are unhappy or disappointed with the AI-powered services they use and would prefer to interact with human support. This study provides a fresh look at how customers' interactions with AI and employee-provided services affect their relationship with the service organisation. Given the importance of staff service in customer reactions and the pervasiveness of AI-powered services within enterprises, this study provides a fresh look at how customers interact with AI and employee-provided services. Customer's participation in the organisation as well as their loyalty behaviours demonstrate customer relationships (Lemon and Verhoef, 2010). This investigation would supplement the previous research on customer engagement by providing additional strategies to encourage customer interaction with the organisation.

Følstad. Nordheim and Bjørkli (2018) led a research entitled "What Makes Users Trust a Chatbot for Customer Service? An Exploratory Interview Study" in their study they explained Chatbots are becoming more popular as a client service option. Users must have faith in chatbots to give the necessary help before they employ them for this purpose. However, there is presently a scarcity of information on the aspects that influence users' confidence in chatbots. They accomplished their aim by presenting an interview study that fills in the gaps in people's expertise. There are thirteen users of Customer service chatbots who were questioned about their experiences with them. The chatbots and the elements that influence their faith in them Users' faith in chatbots Customer service was shown to be influenced by (a) elements related to the individual product. The quality of the chatbot's understanding of requests and advice, in particular, not just in terms of human-likeness, self-presentation, and professional look, but also in terms of (b) as a result of service-related considerations. In response to the question of research, they preferred to choose and definable design of research. Precisely, to accumulate insights that are rich in depth they carried out a semi-planned interview study. They start with a summary of the participants' replies to the subjects of perceived advantages and limitations of chatbots for customer support in the findings section. Then they go on to the area that corresponds to the study question – variables impacting confidence. Some of the benefits of chatbots as described by them in this study were help and information was fast and easily accessible and the response was also rapid another benefit waste also worked perfect for simple and some common questions and provide answers to those questions who have passed by the substantial quality control. According to them, there were some limitations of this research as well. They explained as the goal of this research was to provide a foundation for understanding customer service chatbot trust. This goal was pursued via exploratory interview research, which resulted in several significant limitations. Three of these restrictions will be addressed in this section. First, the survey is tiny in scope, with just 13 people using chatbots for customer assistance. Due to this constraint, they were able to investigate a variety of characteristics that may influence chatbot trust. Simultaneously, the generality of the discovered criteria may be questioned. Future research is required to confirm and expand on the results of this study, which will need the participation of a greater number of users. Second, the research is carried out in a particular setting: four Norwegian customer service chatbots. Because of this constraint, they were able to conduct a thorough investigation of the user experience and trustworthiness of these chatbots. Furthermore, the environment they chose enabled them to conduct the research in a market where digital technology adoption is strong, which is favourable to the results' relevancy. Simultaneously, comparable data sets in other marketplaces should be added to the research. Third, since the study's goal was exploratory, the data collection and analysis were not directed by particular theoretical conceptions of chatbot trust. This constraint arises from the study's status as a first step toward gaining a better understanding of the subject. The use of a theoretical framework to guide future research will be beneficial. Hopefully, the findings of this research will serve as a foundation for developing such a framework. They've provided experimental interview research that sheds insight on the aspects that influence chatbot users' trust. Not only do the identified variables apply to chatbots, but also to the service context in which they are used. The outcomes of the research are presented as a first step in developing a framework for consumer service chatbot confidence. The results also have a variety of ramifications for chatbot designers and developers. Chatbots must be trusted by users in order to fully achieve their potential for customer service. They believe that such a discovery will spur more study in this crucial sector.

Ameen et al. (2021) led research entitled “Customer experiences in the age of artificial intelligence.” The way people engage with companies is changing because of artificial intelligence (AI). There is a scarcity of empirical research on AI-assisted consumer interactions. As a result, the goal of this research is to see how integrating AI into shopping might lead to a better AI-enabled consumer experience. The confidence theory and the quality of service concept are used to develop a theoretical model. Consumers who utilised a beauty product's AI-enabled application were asked to complete an online survey. Partial least structural model was used to analyse a total of 434 answers. The results show that perceived sacrifice and trust play an important role in moderating the impacts of perceived convenience, personalization, and AI-enabled service excellence. The results also show that relationship commitment has a major impact on AI-enabled customer experience. This research adds to the previous literature by highlighting the mediating impacts of trust and perceived sacrifice on AI-enabled customer experience, as well as the direct influence of relationship commitment. Furthermore, the research has practical consequences for merchants that use AI in their client services. All of the components' assessment items were taken from past research: AI-enabled consumer experience, AI-enabled quality of service, relationship quality, trustworthiness, perceived ease, personalization, and perceived compromise. Each aspect was assessed using a variety of items. A seven-point Likert scale with anchors ranging from "strongly disagree" to "strongly agree" was used for each topic. They concluded finally that there study was a huge contribution towards understanding of AI technology. Their research is a pioneering attempt to examine how a cutting-edge technology, artificial intelligence, might enhance the purchasing experience for customers by stressing the hedonic and recognition components of AI-enabled customer encounters. In AI-enabled customer experience, their research also reveals the beneficial function of relationship commitment, as well as the major mediating effects of trust and perceived sacrifice.

### 2.3 Customer Engagement with AI Features

Customer engagement is a sort of co-creation between service providers and their consumers that has been identified as a marketing approach to increase customer purchase and loyalty (Brodie et al., 2011; Hoyer et al., 2010; Nambisan and Nambisan, 2008). Because the amount of involvement with a service organisation and its linked enterprises has financial ramifications for the organisation as well as for clients, this notion has gained widespread acceptance in marketing literature (Doorn et al., 2010). Customer engagement has been conceptualised in a variety of ways due to the fact that it is a relatively new idea. As a result, there is variability in both the drivers and the results of the literature. In accordance with the relevant literature, customer engagement is defined as the sum of a customer's behavioural, cognitive, and emotional involvement with a company (Hollebeek, 2011b; Prentice et al., 2018, 2019b). They also examined consumer engagement from the viewpoints of emotive, cognitive, and psychological factors. Customer identification, which indicates their perceived oneness with or belongingness to the brand or organisation; attention, which indicates their attention, focus, and connection with the brand or organisation; enthusiasm, which indicates customers' exuberance and interest; absorption, which indicates customers' pleasant state of mind; and interaction, which indicates customers' participation with the brand or organisation were included in this assessment. Each dimension has its own set of antecedents and consequences (Hollebeek, 2011a).

Customers' negative emotions may colour their perceptions of the company and interactions with employees. While some customers may be unhappy with the service they received, others may sympathise with the employees. This response is reflected in their emotional talents, which combine to form their emotional intelligence. The concept of emotional intelligence in the context of an organisational setting has received a lot of attention over the last three decades as a critical component of individual and organisational results. Emotional intelligence is regarded as a type of human intelligence. There has been no research to date into how customers' emotional intelligence affects the quality of service they receive and their relationship with the company that provides that service. More specifically, how such human and machine intelligences (AI) might be combined to improve an organization's performance (Prentice et al., 2013).

An artificial intelligence-based marketing analytics tool can determine whether or not a product design is suitable for meeting the needs of customers and, as a result, whether or not customers are satisfied (Dekimpe, 2020). Topic modelling improves the system's capabilities in terms of service innovation and design (Antons & Breidbach, 2018). The preference weight assigned to product attributes during product search helps marketers understand the product recommender system and align marketing strategies for meaningful product management (Dzyabura & Hauser, 2019). Deep learning allows for the personalization of point of interest recommendations, which also aids in the exploration of new locations (Guo et al., 2018). Artificial intelligence's capabilities enable services and products to be tailored to the specific needs of individual customers (Kumar et al., 2019).

AI can better understand consumers' online information search and product selection habits in order to provide a more personalised shopping experience (Rust and Huang, 2014). It's an excellent opportunity for online merchants to analyse the profiles of existing and prospective customers and so recommend tailored marketing offerings (Onete, Constantinescu and Filip, 2008). Additionally, AI enables constant and interactive engagement with both customers and employees. A chatbot can automate frequently asked questions (FAQs) about products, their use, and the purchase procedure. Automated algorithms are used in new sales models to promote unique, personalised marketing products, enhancing consumer happiness and engagement. The most up-to-date methods for enhancing the overall quality of the customer experience are those that are powered by AI and include data science and emerging technologies such as extended reality, robots, recommender systems, the internet of things, and conversational agents, amongst others. A survey conducted by Bain & Company found that the majority of companies already use AI-based customer experience tools in order to maintain a sustainable competitive advantage (Toit, 2020).

Consumer confidence, according to Kim, Ferrin, and Rao (2008), has a favourable effect on a consumer's propensity to purchase. The more trust a consumer has in an online store, the more likely the consumer will complete the purchase process. When a customer senses a financial risk, trust is critical. Hoy, (2018) in the work on, “Alexa, Siri, Cortana, and more: An introduction to voice assistants” tells that using artificial intelligence to provide novel features and simple solutions for everyday activities has transformed the digital world and shaped the web and mobile marketplaces. Examples include face recognition, voice assistants like "Siri, Alexa, and Cortana, bright selfies, and augmented reality, among other things." Amazon and Netflix are already utilizing machine learning to target specific customers with advertisements. Smartphone manufacturers are actively enhancing their gadgets by including dedicated artificial intelligence processors. Specialized hardware is built into the latest

"Samsung Galaxy, Google Pixel, and Apple iOS smartphones" with the goal of increasing the efficiency with which AI-based operations can be handled. Despite the fact that this capability was present in only 3 percent of phones in 2017, it is expected to be present in approximately 35 percent of all mobile devices sold in 2018.

Thatcher et al. (2013) classified trust into two categories: general and particular trust. The term "general trust" refers to the e-commerce environment, as well as customer perceptions and attitudes regarding it. Specific trust is associated with a certain virtual store shopping experience. Confidence can be increased by interactive communication between the store and the buyer, which includes the use of appropriate product descriptions and visuals that minimise perceived risk. As Cătoiu et al. (2014) point out, there is a substantial inverse relationship between perceived risks and trust.

Lee et al. (2008) examined the effect of negative online customer reviews on consumer product attitudes and discovered that a large proportion of unfavourable online consumer reviews leads in a conformity effect. It is possible that bad online reviews have an effect on real purchasing behaviour or at the very least purchase intention. Gacanin and Wagner (2019) explained the difficulties associated with implementing autonomous customer experience management (CEM). The report also described how artificial intelligence and machine learning were employed to build an intelligence network that was a substantial economic value generator. An artificial intelligence-powered chatbot that makes use of Natural Language Processing has improved the client experience (NLP). Artificial intelligence and machine learning algorithms aided in the efficient processing of data, allowing us to reach the most appropriate conclusion. Customer service is crucial in distinguishing between customers' perceptions of the organization's service excellence and the perceptions of other employees. Customer service experiences are being influenced by artificial intelligence (AI), according to recent research (Xiang et al., 2015). Artificial intelligence-powered services are becoming increasingly prevalent in business processes as a cost-effective solution to improve organizational efficiency and service delivery (e.g. providing convenience to customers by using 24-h auto-messaging services).

Doorn et al. (2010) explored the other side of this area and led a research entitled "Customer engagement behaviour: theoretical foundations and research directions". they provided a different point of view from a consumer, company, and context-based viewpoint, presented a complete conceptual framework to identify its components, antecedents, and repercussions Consumer determinants (such as contentment, trust, and commitment) might be the consequence of the firm's activities. Governmental, financial, societal, and technical context-based elements may be opportunist and uncontrolled. According to this research, organization-based motivations are more appealing when it comes to attracting consumer participation through providing a pleasant customer experience. Even though each interaction with the organisation contributes to the overall customer experience, in people-intensive industries, the moment of truth is the service encounter with an employee service representative, which is critical to the customer's perception of a company's service quality and their willingness to engage with the firm's products and services (Prentice, 2016). Employee service is the first and most important point of contact for the client before, during, and after the service process is completed. This interaction has a significant impact on consumers' impressions of any service encounter and is critical in determining the amount of perceived service quality a customer perceives (Prentice, 2013a, 2013b, 2019). Customers often rely their opinion of an organisation mainly on the service they get from customer contact staff, and communication between an employee and a client is a mutually participatory process that requires both parties to participate (Prentice, 2019).

Ojapuska (2018) whose research was entitled as "the impacts of chatbots in customer engagement" states that in today's world's consumer a rapid and personalized service that may or might not involve interactions with human beings. It also states that businesses are quickly using chatbots to increase customer connection, customer engagement, the purchasing process, and the automated resolution of recurrent enquiries, all of which lead to a pleasant customer experience.

Brandtzaeg And Følstad (2017) explored about uses of chatbots in their paper entitled as "why people use chatbots, conference paper, internet sciences" People are interested in using chatbots because they are productive in that they make it easier to access information, speed up operations, and are available 24 hours a day, seven days a week. It goes on to say that consumers find interacting with chatbots fun and that it is a standard customer service, which sums up the main motivations pushing organisations to employ chatbots to improve customer experience. Personalized marketing is a kind of target marketing that makes use of pieces of data and automated to deliver tailored content to consumers in order to increase engagement and improve the customer experience.

André et al. (2017) entitled "Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data" discusses how current innovations in artificial intelligence-driven marketplaces and micro-targeting of consumers have assisted in individualising content suggestion for customers, hence making the options more customised and easier to pick from.

Personalization in marketing, according to a report by James (2018) which was given the title "Artificial Intelligence in Marketing", aids in addressing specific consumer wants throughout the customer journey while without breaching the client's privacy. The notion of hyper-personalization is explained in detail in order for marketers to better grasp their customers' viewpoints and optimise their marketing methods. According to the study by Zumstein and Hundertmark (2017) entitled as "Chatbots – An interactive technology for personalized communication, transactions and services" and "Using Learning Analytics to Understand the

Design of an Intelligent Language Tutor" respectively., chatbots aid in the provision of individualised connection with clients, allowing them to reach out to the company at any time and from any location. It also discusses how chatbots assist in the collecting of consumer data regarding product, service, and content preferences, use patterns, and the creation of additional user contact points to increase convenience, as well as the provision of tailored service using deep learning.

Many studies have revealed that the vast majority of users are unsatisfied or frustrated with AI-powered services and prefer personal interactions with human customer service representatives (Nanji, 2019). As a result of the importance of staff service in determining customer reaction and the widespread use of artificial intelligence-powered services within enterprises, this study provides a fresh perspective on how customers' experiences with artificial intelligence and employee-provided services affect their relationship with the service organization. Participants in an organization's activities and loyalty behaviors are examples of how customers demonstrate their relationships with the organization. This analysis would be a significant contribution to the study of customer engagement and the development of additional measures to stimulate consumer involvement with an organization.

Hancock et al. (2011) found a number of factors that contribute to such trust, categorising them as human-related, robot-related, and environmental. Corritore et al. (2003) established a widely acknowledged theory of trust in interactive systems, focusing on users' trust in websites. Credibility, ease-of-use, and risk were identified as critical determinants of trust in this paradigm. While the concept of trust in technology is controversial (Fryer and Carpenter, 2006), there is a growing amount of study on the subject. For instance, in a review paper on robot trust. Trust has been studied historically in relation to interpersonal relationships, organisations, and society (Rousseau, et al., 1998), and is frequently described as inducing a sense of belonging (Schoorman, et al., 2007) and facilitating frictionless interaction and collaboration between humans (Botsman, 2017). Mayer et al. (1995), in one of the most widely used models of organisational trust, identified three critical drivers of trust, namely the trustee's opinions of the trustor's expertise, compassion, and integrity.

When developing strategies and planning marketing activities, marketers can benefit from using artificial intelligence to help with segmentation, targeting, and positioning (STP). In addition to STP, artificial intelligence can assist marketers in visualising the strategic orientation of the company (Huang & Rust, 2017). Text mining and machine learning algorithms have the potential to be utilised in a wide range of industries, including banking and finance, art marketing, retail, and tourism, in order to locate customer segments that are most likely to generate a profit (Dekimpe, 2020; Netzer et al., 2019; Pitt et al., 2020; Valls et al., 2018). The pool of customers that are targeted can be narrowed down even further by using a combination of data optimization techniques, machine learning, and causal forests (Chen et al., 2020; Simester et al., 2020).

Bloom's taxonomy of educational learning objectives was revised by Anderson and Krathwohl (2001) to place creation at the top of the hierarchy as the most important learning objective (Bloom et al., 1956). This was achieved through the revised version of Bloom's taxonomy that they created. They explain it as "putting elements together to form a coherent or functional whole; reorganizing elements into a new pattern or structure." "Putting elements together to form a coherent or functional whole." Bringing together disparate elements to form a whole that is either coherent or functional will demonstrate that the most significant factor that differentiates AI algorithms from conventional statistical methods is the idea of knowledge creation as it relates to Anderson's taxonomy. The authors argue that making such a distinction has significant implications for the likelihood of adopting AI technologies in aspects of marketing that require knowledge transfer or stand to benefit from it. Deep artificial neural networks are the primary focus of the vast majority of artificial intelligence applications in the business world. These networks are utilised to solve challenging predictive problems that were thought to be unsolvable in the past. Marketers can use predictive analytics to forecast future marketing actions and how those actions will impact behavior, generate insights to improve leads, acquire new customers, and achieve pricing optimization, among other things. They can also use predictive analytics to forecast how those actions will impact pricing (Murray & Wardley, 2014; Power, 2016). Researchers and managers in the field of marketing frequently establish objectives such as the maximisation of profit and market share, product cannibalization, customer retention, and utility maximisation (for examples, see Gonül and Hofstede, 2006; and Natter et al., 2007). Defining a holistic objective function is essential, however, because an AI algorithm is not restricted by common sense and does not have to operate within the confines of a predefined set of features or model specifications. This makes it possible for the algorithm to operate more freely.

The term "hassle-free service" refers to a service that is trouble-free, methodical, and problem-free, and in which the customers' demands are met without the presence of obstacles or confusion. Using blended artificial intelligence (AI), which is a combination of artificial intelligence and human intelligence, as well as data analytics, the articles by Görgens (2019) entitled “How can Artificial Intelligence use big data to form a better customer experience” and “Artificial Intelligence – Creating automated insights for customer relationship management.” AI (artificial intelligence) enables data analysis and individualised consumer experiences that would not be possible without machine learning's efficiency and efficacy. However, several earlier authors have noted a perceived lack of human touch, and additional investigation has revealed that data privacy is a big worry for customers. Clients are aware that businesses utilise their information to target them with customised advertisements. They do not, however, like to share their data with third parties and have little faith in organisations with regard to their information. As a result, Blended AI has been promoted as a panacea for all issues. Blended artificial intelligence is a synthesis of machine and human intellect. In the finalisation stage, an agent is utilised to conduct the final analysis of the data for clients. That way, organisations regain their human touch, communication is more transparent, and data is obtained with permission. As a result, data privacy could be restored. Consumer relationship management is critical for businesses, as the customer adds value to the corporation, whether economically or emotionally.

### 2.4 Virtual Agents

Virtual agents, also referred to as chatbots or AI agents, are artificial intelligence (AI) systems designed to interact with humans in a natural, human-like manner (Justo et al., 2018). They are typically used in a variety of contexts, including customer service, e-commerce, and healthcare, to provide information, answer queries, and guide users through various processes (Ben Saad & Choura, 2023).

One of the key features of virtual agents is their ability to understand and respond to natural language. This is made possible through the use of natural language processing (NLP), a branch of AI that enables machines to interpret and generate human language (Justo et al., 2018). This capability allows virtual agents to understand user queries, regardless of how they are phrased, and to provide appropriate responses.

Virtual agents are also characterized by their ability to provide personalized service. By leveraging machine learning algorithms, virtual agents can learn from past interactions, understand user preferences, and provide personalized recommendations (Ben Saad & Choura, 2023). This ability to provide personalized service can significantly enhance the user experience and improve customer satisfaction.

Furthermore, virtual agents are capable of operating 24/7, ensuring that user queries are addressed promptly, regardless of the time of day (Söderlund & Oikarinen, 2021). This round-the-clock service can significantly enhance customer satisfaction, particularly in sectors such as e-commerce and customer support where timely response is critical.

Virtual agents are AI systems designed to interact with humans in a natural, human-like manner. They are characterized by their ability to understand and respond to natural language, provide personalized service, and operate 24/7. As AI technology continues to evolve, it is anticipated that the capabilities of virtual agents will continue to expand, further enhancing their potential benefits.

### *2.4.1 Role of AI in Virtual Agents*

Artificial Intelligence (AI) plays a pivotal role in the functionality and effectiveness of virtual agents. These AI-powered entities, also known as chatbots or AI agents, leverage advanced AI technologies to interact with users in a human-like manner, providing personalized responses, learning from past interactions, and making intelligent decisions.

One of the primary roles of AI in virtual agents is enabling natural language processing (NLP). NLP is a branch of AI that allows machines to understand, interpret, and generate human language. This technology enables virtual agents to understand user queries, regardless of how they are phrased, and provide appropriate responses. This capability is crucial for enhancing the user experience and ensuring effective communication between the virtual agent and the user (Justo et al., 2018).

AI also enables virtual agents to provide personalized service. By leveraging machine learning algorithms, virtual agents can learn from past interactions, understand user preferences, and provide personalized recommendations. This capability can significantly enhance the user experience and improve customer satisfaction. For instance, Ben Saad and Choura (2023) found that virtual recommendation agents, powered by AI, could effectively guide consumers in their purchase decisions, thereby enhancing customer satisfaction.

Furthermore, AI enables virtual agents to make intelligent decisions. For instance, in a customer service scenario, an AI-powered virtual agent can analyze a customer's query, determine the best course of action, and either provide a solution or escalate the issue to a human agent. This decision-making capability can significantly enhance the efficiency and effectiveness of customer service (Söderlund and Oikarinen, 2021).

AI also plays a crucial role in the continuous improvement of virtual agents. Through machine learning, virtual agents can learn from their interactions with users, continuously improving their performance over time. This capability is crucial for ensuring that virtual agents remain effective and relevant in the face of changing user needs and expectations (Contreras & Valette-Florence, 2023).

AI plays a pivotal role in the functionality and effectiveness of virtual agents. By enabling natural language processing, personalization, intelligent decision-making, and continuous learning, AI ensures that virtual agents can provide a high-quality, human-like interaction experience. As AI technology continues to evolve, it is anticipated that the capabilities of virtual agents will continue to expand, further enhancing their potential benefits.

### *2.4.2 Virtual Agents in Different Sectors*

The use of virtual agents has permeated various sectors, demonstrating the versatility and adaptability of this technology. The use of virtual agents in different sectors underscores the versatility and adaptability of this technology. Whether in e-commerce, education, healthcare, or tourism, virtual agents have demonstrated their potential in enhancing customer service, improving user engagement, and transforming traditional business models. As technology continues to evolve, it is anticipated that the application of virtual agents will become even more widespread, permeating other sectors and revolutionizing the way we interact with digital platforms.

In the e-commerce sector, virtual agents have been utilized to enhance customer service and improve the overall shopping experience. Antonescu, Barbu, and Luchian (2017) explored the integration of e-commerce in the tourism industry, highlighting the role of virtual agents in facilitating transactions and providing personalized recommendations to customers. Their study underscores the potential of virtual agents in transforming traditional business models and enhancing customer engagement in the digital landscape.

In the realm of education, virtual agents have been employed to facilitate adaptive learning. Kazoun, Kokkinaki, and Chedrawi (2022) investigated the factors affecting the use of AI agents in adaptive learning in the higher education sector. Their research revealed that AI agents could provide personalized learning experiences, thereby improving student engagement and learning outcomes. This finding suggests that virtual agents could play a crucial role in the future of education, particularly in the context of online learning and distance education.

The healthcare sector has also witnessed the integration of virtual agents, particularly in patient care and health management. Kocakoç (2022) discussed the role of artificial intelligence in healthcare, emphasizing the potential of virtual agents in improving patient care. Virtual agents can provide health advice, facilitate appointment scheduling, and monitor patient health, thereby enhancing the efficiency and effectiveness of healthcare services. This research highlights the transformative potential of virtual agents in healthcare, a sector that is increasingly embracing digital technologies.

In the tourism industry, virtual agents have been used to enhance customer service and provide personalized travel recommendations. Antonescu et al. (2017) examined the use of e-commerce in the tourism industry, highlighting the role of virtual agents in facilitating transactions and enhancing customer engagement. Their study underscores the potential of virtual agents in transforming the tourism industry, particularly in the context of online booking and travel planning.

The service sector has been significantly transformed by the advent of virtual agents, with these AI-powered entities playing a crucial role in enhancing customer service and improving operational efficiency. Virtual agents, with their ability to provide round-the-clock service, handle multiple queries simultaneously, and offer personalized responses, have become an integral part of the service industry.

In the realm of customer service, virtual agents have been employed to provide immediate responses to customer queries, thereby enhancing customer satisfaction and loyalty. For instance, Söderlund and Oikarinen (2021) examined the role of perceived humanness in virtual agents as a source of customer satisfaction in the service sector. Their study revealed that customers tend to be more satisfied when they perceive virtual agents as more human-like, underscoring the importance of designing virtual agents that can mimic human interaction effectively.

Virtual agents have also been used to mitigate negative effects when service fails. Sands, Campbell, Plangger, and Pitt (2022) explored the role of virtual service agents, or "buffer bots," in mitigating the negative effects of service failure. Their study found that virtual agents could effectively manage customer complaints and reduce customer dissatisfaction, highlighting the potential of virtual agents in crisis management.

In the context of sales, virtual agents have been employed to enhance interaction between salespeople and consumers. Ben Saad and Choura (2023) investigated the role of virtual recommendation agents in improving the interaction between salespeople and consumers. Their study found that virtual agents could effectively guide consumers in their purchase decisions, thereby enhancing sales performance and customer satisfaction.

Furthermore, virtual agents have been used to facilitate online shopping, particularly during the Covid-19 crisis. Saad and Choura (2022) explored the impact of anthropomorphic virtual agents on consumers' psychological states during online shopping amid the pandemic. Their study revealed that virtual agents could effectively alleviate consumers' anxiety and enhance their shopping experience, underscoring the potential of virtual agents in facilitating online shopping in times of crisis.

Virtual agents have significantly transformed the service sector, enhancing customer service, improving operational efficiency, and facilitating online shopping. As technology continues to evolve, it is anticipated that the role of virtual agents in the service sector will become even more crucial, driving innovation and improving customer experience.

### *2.4.3 Impact of Virtual Agents on User Experience*

The user experience, a critical factor in the success of any digital interaction, has been significantly influenced by the advent of virtual agents. These AI-powered entities have been instrumental in shaping the way users interact with digital platforms, affecting various aspects of the user experience, from engagement and satisfaction to trust and perceived value.

One of the key areas where virtual agents have made a significant impact is in enhancing user engagement. For instance, Ben Mimoun, Poncin, and Garnier (2012) conducted a study on embodied virtual agents, analyzing the reasons for their failure. They found that the success of virtual agents largely depends on their ability to engage users effectively. This finding underscores the importance of designing virtual agents that can capture and sustain user attention, thereby enhancing user engagement.

Virtual agents have also been found to influence user satisfaction. Söderlund and Oikarinen (2021) examined how perceived humanness in virtual agents could source customer satisfaction. They found that users tend to be more satisfied when they perceive virtual agents as more human-like. This finding suggests that the design of virtual agents, particularly their ability to mimic human interaction, plays a crucial role in shaping user satisfaction.

In terms of trust, Callebert, Lourdeaux, and Barthes (2016) explored the role of trust-based decision-making systems in action selection by autonomous agents. Their study revealed that trust plays a critical role in the interaction between humans and virtual agents, affecting user acceptance and adoption of these agents.

The perceived value of the online visit has also been found to be influenced by virtual agents. Charfi and Lombardot (2015) investigated the impact of e-atmospheric elements on the perceived value of the online visit. They found that virtual agents, as part of the e-atmospheric elements, can significantly enhance the perceived value of the online visit, thereby improving the overall user experience.

Virtual agents have a significant impact on the user experience, influencing user engagement, satisfaction, trust, and perceived value. As such, the design and implementation of virtual agents should be carefully considered to ensure that they enhance, rather than detract from, the user experience. Future research should continue to explore the impact of virtual agents on the user experience, with a focus on understanding how these agents can be optimized to meet the evolving needs and expectations of users.

### *2.4.4 Impact of Virtual Agents on Customer Satisfaction*

Customer satisfaction, a key determinant of business success, has been significantly influenced by the advent of virtual agents. These AI-powered entities have the potential to enhance customer satisfaction by providing personalized, efficient, and round-the-clock service.

One of the primary ways in which virtual agents can enhance customer satisfaction is through their ability to provide immediate responses to customer queries. In today's fast-paced digital world, customers expect quick and efficient service. Virtual agents, with their ability to provide instant responses, can meet these expectations, thereby enhancing customer satisfaction. For instance, Söderlund and Oikarinen (2021) found that customers tend to be more satisfied when they perceive virtual agents as more human-like, underscoring the importance of designing virtual agents that can mimic human interaction effectively.

Virtual agents can also enhance customer satisfaction by providing personalized service. By leveraging AI and machine learning technologies, virtual agents can understand customer preferences and provide personalized recommendations, thereby enhancing customer satisfaction. For example, Ben Saad and Choura (2023) investigated the role of virtual recommendation agents in improving the interaction between salespeople and consumers. Their study found that virtual agents could effectively guide consumers in their purchase decisions, thereby enhancing sales performance and customer satisfaction.

Furthermore, virtual agents can enhance customer satisfaction by providing round-the-clock service. Unlike human agents, virtual agents can operate 24/7, ensuring that customer queries are addressed promptly, regardless of the time of day. This round-the-clock service can significantly enhance customer satisfaction, particularly in sectors such as e-commerce and customer support where timely response is critical.

However, it's important to note that the impact of virtual agents on customer satisfaction is not always positive. If not properly designed or implemented, virtual agents can lead to customer frustration and dissatisfaction. For instance, Ben Mimoun, Poncin, and Garnier (2012) conducted a case study on embodied virtual agents, analyzing the reasons for their failure. They found that issues such as poor interaction design and lack of human-like qualities could lead to customer dissatisfaction.

While virtual agents have the potential to significantly enhance customer satisfaction, their design and implementation need to be carefully considered. Factors such as response time, personalization, availability, and human-like interaction play a crucial role in determining the impact of virtual agents on customer satisfaction. As such, businesses looking to implement virtual agents should focus on these factors to ensure that their virtual agents enhance, rather than detract from, customer satisfaction.

#### *2.4.5 Factors Influencing the Adoption and Effectiveness of Virtual Agents*

The adoption and effectiveness of virtual agents are influenced by a myriad of factors, ranging from their perceived usefulness and ease of use to their design and interaction style. Understanding these factors is crucial for the successful implementation of virtual agents and for maximizing their potential benefits.

Perceived usefulness and ease of use are among the most significant factors influencing the adoption of virtual agents. According to the Technology Acceptance Model (TAM), users are more likely to adopt a technology if they perceive it as useful and easy to use (Davis, 1989). This model has been applied to the context of virtual agents by several studies. For instance, Brachten, Kissmer, and Stieglitz (2021) conducted a survey study on the acceptance of chatbots in an enterprise context. They found that perceived usefulness and ease of use were significant predictors of chatbot acceptance, underscoring the importance of these factors in the adoption of virtual agents.

The design and interaction style of virtual agents also play a crucial role in their effectiveness. Justo et al. (2018) explored how ontologies could improve the empathy of interactive bots. They found that the design of virtual agents, particularly their ability to mimic human-like empathy, significantly influenced their effectiveness. Similarly, Söderlund and Oikarinen (2021) found that the perceived humanness of virtual agents was a significant source of customer satisfaction, suggesting that the design of virtual agents should aim to mimic human-like interaction as closely as possible.

Social influence is another factor that can influence the adoption of virtual agents. According to the Social Influence Theory, individuals are more likely to adopt a behavior if they perceive that it is socially accepted or endorsed (Kelman, 1958). In the context of virtual agents, Contreras and Valette-Florence (2023) proposed a theoretical model of branded chatbot adoption, using a bibliometric and machine learning perspective. They found that social influence was a significant predictor of chatbot adoption, suggesting that the social acceptance of virtual agents can influence their adoption.

The adoption and effectiveness of virtual agents are influenced by various factors, including perceived usefulness, ease of use, design, interaction style, and social influence. Understanding these factors is crucial for the successful implementation of virtual agents and for maximizing their potential benefits. Future research should continue to explore these factors, with a focus on understanding how they can be optimized to enhance the adoption and effectiveness of virtual agents.

### *2.4.6 Challenges in the Adoption of AI-Enabled Virtual Agents*

While AI-enabled virtual agents offer numerous benefits, their adoption is not without challenges. These obstacles range from technical and design issues to concerns about privacy and trust, and they must be addressed to fully realize the potential of this technology.

One of the primary challenges in adopting AI-enabled virtual agents is the complexity of their design and implementation. Creating a virtual agent that can understand and respond to natural language, learn from interactions, and make intelligent decisions requires advanced AI and machine learning technologies. This complexity can make the design and implementation process time-consuming and costly, particularly for small and medium-sized enterprises that may lack the necessary resources and expertise (Brachten, Kissmer, & Stieglitz, 2021).

Another significant challenge is ensuring the quality of the interaction between the virtual agent and the user. For a virtual agent to be effective, it must be able to mimic human-like interaction as closely as possible. However, achieving this level of realism can be challenging. If a virtual agent fails to understand a user's query or provides inappropriate responses, it can lead to user frustration and dissatisfaction (Ben Mimoun, Poncin, & Garnier, 2012).

Privacy and trust are also major concerns in the adoption of AI-enabled virtual agents. Users may be hesitant to interact with virtual agents due to concerns about the privacy of their data. They may also lack trust in the ability of virtual agents to provide accurate and reliable information or advice. Building trust and ensuring data privacy are therefore crucial for the successful adoption of virtual agents (Callebert, Lourdeaux, & Barthes, 2016).

Finally, there is the challenge of social acceptance. Despite the advancements in AI technology, some users may still prefer human interaction over interaction with a machine. Overcoming this resistance requires efforts to educate users about the benefits of virtual agents and to design virtual agents that are as human-like as possible (Contreras & Valette-Florence, 2023).

While AI-enabled virtual agents offer numerous benefits, their adoption is not without challenges. Overcoming these obstacles requires a combination of technological innovation, careful design, user education, and efforts to build trust and ensure privacy. As the field of AI continues to evolve, it is anticipated that these challenges will be increasingly addressed, paving the way for wider adoption of virtual agents.

**2.5 Summary**

The literature review explored the role, impact, and challenges of virtual agents in various sectors, with a particular focus on the service sector. Virtual agents, powered by artificial intelligence (AI), have been found to significantly enhance customer satisfaction by providing immediate responses, personalized service, and round-the-clock availability (Söderlund & Oikarinen, 2021; Ben Saad & Choura, 2023).

In the service sector, virtual agents have been used in a variety of contexts, including customer service, e-commerce, and healthcare. They have been found to improve efficiency, reduce costs, and enhance customer satisfaction (Söderlund & Oikarinen, 2021; Ben Saad & Choura, 2023). However, the adoption of virtual agents in the service sector is not without challenges. These include technical and design complexities, concerns about privacy and trust, and social acceptance (Brachten, Kissmer, & Stieglitz, 2021; Callebert, Lourdeaux, & Barthes, 2016).

The literature also highlighted the impact of virtual agents on user experience. Virtual agents have been found to enhance user experience by providing personalized, efficient, and human-like interaction. However, if not properly designed or implemented, virtual agents can lead to user frustration and dissatisfaction (Ben Mimoun, Poncin, & Garnier, 2012).

The review also explored the factors influencing the adoption and effectiveness of virtual agents. These include the quality of interaction, personalization, availability, and human-like interaction. However, there are challenges in the adoption of AI-enabled virtual agents, including design and implementation complexity, interaction quality issues, and concerns about privacy and trust (Brachten, Kissmer, & Stieglitz, 2021; Callebert, Lourdeaux, & Barthes, 2016).

While virtual agents offer numerous benefits, their adoption is not without challenges. Overcoming these challenges requires a combination of technological innovation, careful design, user education, and efforts to build trust and ensure privacy. As the field of AI continues to evolve, it is anticipated that these challenges will be increasingly addressed, paving the way for wider adoption of virtual agents.

Despite the growing body of literature on virtual agents, there remain several research gaps that justify the need for a study on the motivations and challenges in the adoption of virtual agents in the services sector.

Firstly, while many studies have explored the impact of virtual agents on customer satisfaction and user experience (Söderlund & Oikarinen, 2021; Ben Saad & Choura, 2023), there is a lack of comprehensive understanding of the motivations behind the adoption of virtual agents in the services sector. Understanding these motivations is crucial for businesses looking to implement virtual agents, as it can provide insights into the potential benefits of this technology and guide the design and implementation process.

Secondly, while the challenges in the adoption of AI-enabled virtual agents have been acknowledged (Brachten, Kissmer, & Stieglitz, 2021; Callebert, Lourdeaux, & Barthes, 2016), there is a need for more in-depth exploration of these challenges, particularly in the context of the services sector. The services sector is characterized by high levels of customer interaction, making it particularly susceptible to the challenges associated with virtual agents, such as issues with interaction quality and concerns about privacy and trust. A detailed understanding of these challenges can help businesses in the services sector to better prepare for the adoption of virtual agents and to develop strategies to overcome these challenges.

Finally, there is a need for more research on the interplay between the motivations and challenges in the adoption of virtual agents. Understanding how these factors interact can provide a more nuanced understanding of the adoption process and can help businesses to balance the potential benefits of virtual agents against the potential challenges.

In conclusion, the existing gaps in the literature justify the need for a study on the motivations and challenges in the adoption of virtual agents in the services sector. Such a study can provide valuable insights for businesses looking to implement virtual agents, guiding the design and implementation process, and helping to maximize the potential benefits of this technology.

# Chapter III – Methodology

## 3.1 Overview of the Research Problem

The adoption of virtual agents in the services sector has emerged as a significant trend due to their potential to enhance customer service, operational efficiency, and overall productivity. However, despite their increasing prevalence, there exists a gap in understanding the motivations driving businesses to adopt these technologies and the challenges they encounter during the adoption process.

The motivations to adopt virtual agents could range from enhancing customer experience, improving service delivery speed, reducing cost, or gaining a competitive edge. Understanding these motivations can provide vital insights into how businesses perceive the benefits of virtual agents, and thus, can guide strategies for wider implementation and acceptance.

Concurrently, the challenges of adopting virtual agents in the services sector are complex and multi-faceted. They may encompass technical issues such as integration with existing systems, maintaining interaction quality, managing customer data privacy, and building user trust. Businesses may also face organizational challenges such as resistance to change, lack of skilled workforce, and high investment costs. These challenges can potentially deter or slow down the adoption of virtual agents, hence understanding them can help businesses to better navigate the implementation process and devise effective strategies to mitigate these challenges.

Furthermore, the interplay between the motivations and challenges is a significant aspect of this research problem. It is crucial to examine how these factors interact and influence the overall decision-making process regarding the adoption of virtual agents. For instance, how does the severity of the challenges impact the perceived benefits and thus influence the adoption decision?

### 3.2 Research Purpose and Questions

The purpose of this research is to delve into an in-depth understanding of the motivations and challenges that are associated with the adoption of virtual agents in the services sector. The study seeks to identify and examine the key motivating factors that drive businesses to adopt virtual agents, the challenges they encounter in the process of adoption, and how these variables impact the overall adoption and implementation of virtual agents in the services sector.

To achieve the research purpose, the following research questions were framed:

1. What specific factors motivate the adoption of virtual agents in the services sector?
2. What are the particular challenges that the services sector encounters in the adoption of virtual agents?
3. How do the identified motivations influence the adoption of virtual agents in the services sector?
4. How do the identified challenges impact the adoption process of virtual agents in the services sector?
5. How do the motivations and challenges interact and what is their combined impact on the adoption of virtual agents in the services sector?

### 3.3 Operationalization of Theoretical Constructs

To study the motivations and challenges in the adoption of virtual agents in the services sector, a theoretical model has been developed, underpinned by the basic premises of two theories –

Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et. al, 2003) and Technology Threat Avoidance Model (TTAT) (Liang & Xue, 2009). Facilitating Conditions, Social Influence, Performance Expectancy, and Effort Expectancy are the variables adopted from UTAUT. Perceived Susceptibility, Perceived Severity and Perceived Threat are the variables adopted from TTAT

The UTAUT component of the framework, proposed by Venkatesh et al. (2003), posits that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) are key determinants of technology acceptance and usage (Venkatesh et al., 2003).

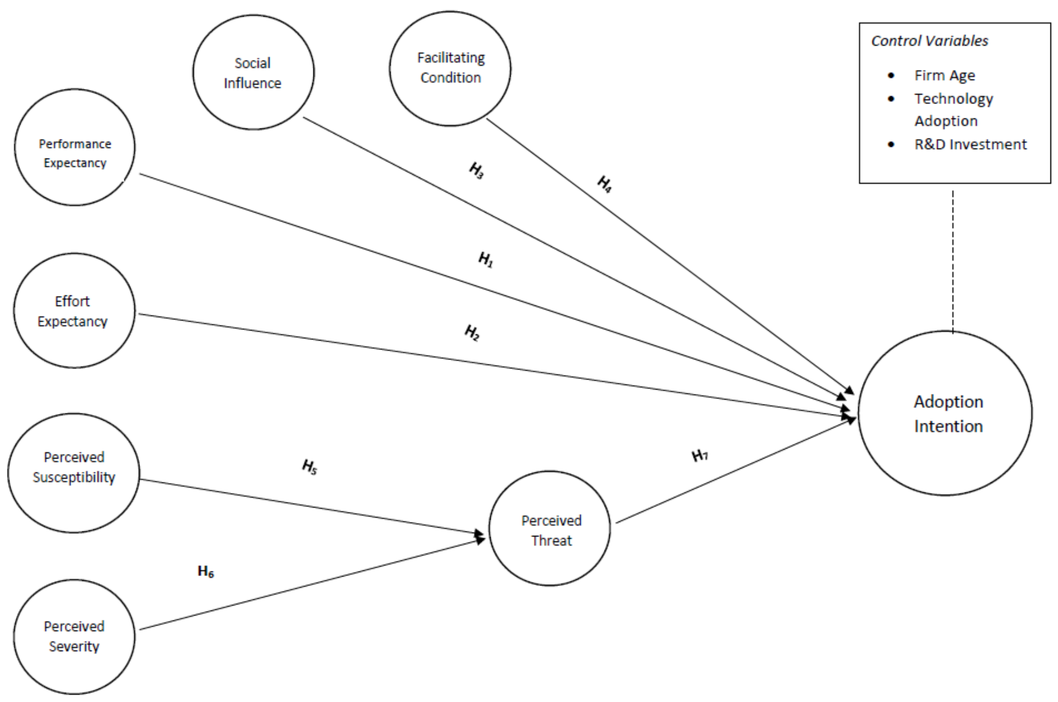
- Performance Expectancy is the degree to which an individual believes that using a particular system would enhance job performance (Venkatesh et al., 2003).
- EE is the degree of ease associated with the use of the system (Venkatesh et al., 2003).
- SI is the degree to which an individual perceives that important others believe he or she should use the new system (Venkatesh et al., 2003).
- FC is the degree to which an individual believes that an organizational and technical infrastructure exists to support the system use (Venkatesh et al., 2003).

On the other hand, the TTAT component, introduced by Liang and Xue (2009), covers the avoidance behaviors in technology adoption, where Perceived Threat (PT) and its susceptibility (PSS) and severity (PSE) play critical roles.

- PSS refers to the subjective assessment of the risk of falling victim to a condition and an individual's feelings of personal vulnerability (Liang & Xue, 2009).
- PSE refers to feelings concerning the ethical and legal consequences of using the technology (Liang & Xue, 2009).

- PT is the extent to which an individual feels threatened by the possibility of negative outcomes from using a system, such as data breaches or other security concerns (Liang & Xue, 2009).

**Figure – 3.1: Theoretical Model of the Study**




## 3.4 Hypotheses of the Study

$H_1$ – Performance Expectancy will have significant influence on the adoption intention of virtual agents

$H_2$ – Effort Expectancy will have significant influence on the adoption intention of virtual agents

$H_3$ – Social Influence will have significant influence on the adoption intention of virtual agents

$H_4$ – Facilitating Conditions will have significant influence on the adoption intention of virtual agents

$H_5$ – Perceived Susceptibility will have significant influence on the perceived threat on the adoption of virtual agents

$H_6$ – Perceived Severity will have significant influence on the perceived threat on the adoption of virtual agents

$H_7$ – Perceived threat will have significant influence on the adoption intention of virtual agents

### 3.5 Instrumentation

| Construct | Indicator | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| Performance Expectancy<br>*(Venkatesh et al., 2012)* | PE01 - I find virtual agents useful in our line of work | | | | | | | |
| | PE02 - Using virtual agents will increase efficiency on the job | | | | | | | |
| | PEO3 - Using virtual agents will increase job productivity | | | | | | | |
| | PE04 – Conversational Virtual Agents would improve the overall customer experience | | | | | | | |
| Effort Expectancy | EE01 – Virtual agents provide accurate context and summarization to continue customer service and interaction | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *(Venkatesh et al., 2012)* | EE02 - Handover and assistance from Virtual agent is smooth and understandable to carry on with the customer interaction | | | | | | | |
| | EE03 - I find virtual agents easy to use | | | | | | | |
| Facilitating Condition<br><br>*(Venkatesh et al., 2012)* | FC01 - I have the necessary resources to use/implement virtual agents | | | | | | | |
| | FC02 – I/My team have the knowledge necessary to use/adopt virtual agents | | | | | | | |
| | FC03 – My company/business unit facilitates the use of virtual agents through various supporting initiatives | | | | | | | |
| | FC04 – I am aware of CHATGPT/Generative AI technologies advancement in Virtual Agents | | | | | | | |
| | FC05 – I have gone through training/facilitation on Generative AI/CHAT-GPT | | | | | | | |
| Social Influence<br><br>*(Venkatesh et al., 2012)* | SI01 - Peers who influence my behavior think that I should use virtual agents. | | | | | | | |
| | SI02 – My peers who use virtual agents have a more positive | | | | | | | |

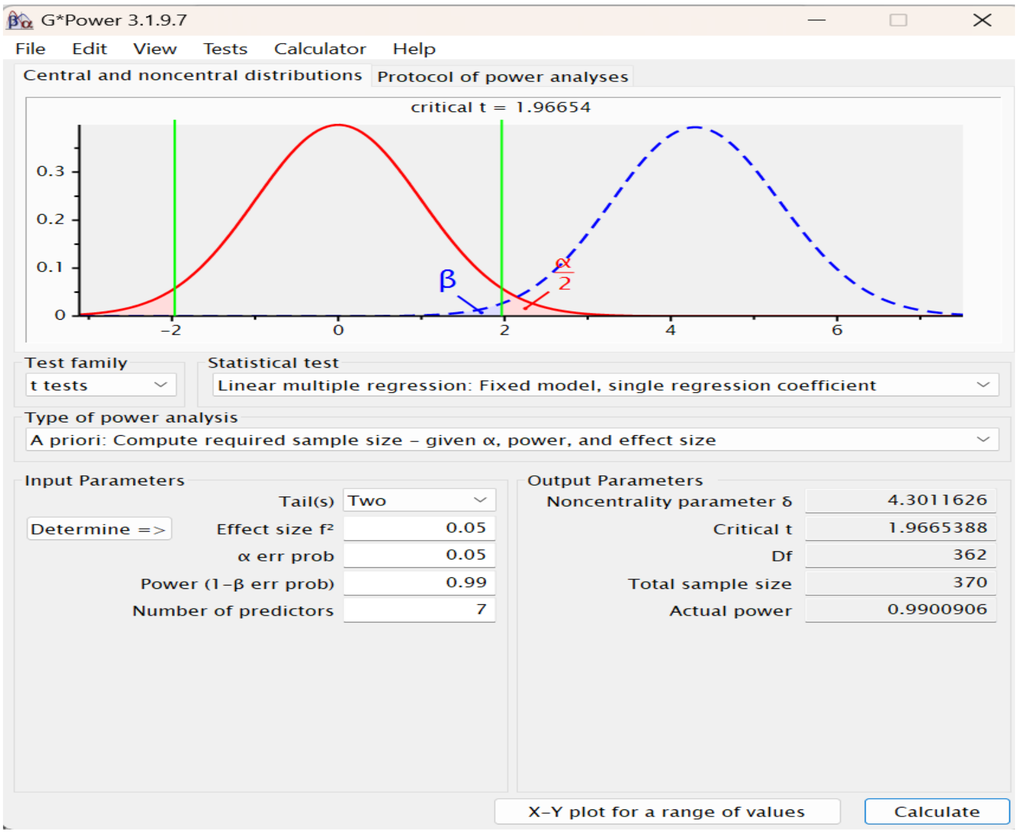
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | attitude towards the use of virtual agents in their job. | | | | | | | |
| | SI03 - People who are important to me think that I should use virtual agents. | | | | | | | |
| Perceived Susceptibility<br>*(Liang & Xue, 2009)* | PS01 – There is a high probability that virtual agents can cause security breaches. | | | | | | | |
| | PSO2 – It is likely that the use of virtual agents will lead to misinformation. | | | | | | | |
| | PSO3 – It is plausible that virtual agents might fail to effectively service clients. | | | | | | | |
| | PS04 - Use of Virtual Agents would risk the reputation of the business | | | | | | | |
| Perceived Severity<br>*(Liang & Xue, 2009)* | PSE01 – If a security breach occurred through a virtual agent, the consequences would be severe. | | | | | | | |
| | PSE02 – Misinformation from virtual agents could have serious repercussions for my job. | | | | | | | |
| | PSE03 – Failure of virtual agents to effectively service clients can have grave implications for the company. | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Perceived Threat<br><br>*(Liang & Xue, 2009)* | PT01 – I am worried that virtual agents might increase the risk to my job security. | | | | | | | |
| | PT02 – I am concerned about the potential threats that virtual agents can bring to our existing systems. | | | | | | | |
| | PT03 – I perceive the adoption of virtual agents as a threat to the quality of service. | | | | | | | |
| Adoption Intention<br><br>*(Venkatesh et al., 2012)* | IU01 – Given the opportunity, I plan to use virtual agents in my tasks. | | | | | | | |
| | IU02 – I am willing to integrate virtual agents into my existing workflow | | | | | | | |
| | IU03 – I could envision adopting virtual agents as a long-term tool for my role. | | | | | | | |

### 3.6 Sample Size

G* Power software has been used to compute the required sample size needed for the proposed research model and the results of the software are shown in Figure 3.2. As the required sample size is 370, to ensure statistical accuracy of the model and to reduce Type I and II error, sample size is fixed at 740 (2 times of the needed sample size). It is believed that the increased sample size will ensure the robustness of the results.

**Figure 3.2: Minimum Sample Size**




## 3.7 Sampling Technique

Purposive sampling technique is used for the study as the respondents must have a reasonable awareness about virtual agents.

## 3.8 Data

The study is mainly based on primary data. The opinions of the respondents are collected using a well-structured and pre-tested questionnaire.

## 3.9 Data Analysis

Due to the complexity of the model, PLS-SEM analysis has been done using SMART PLS software.

# Chapter IV – Results & Analysis

In order to satisfy the objectives of the study, required data were collected from 628 respondents using a well-structured and pre-tested schedule questionnaire. It could be noted that, purposive sampling has been used for the study, as answering the questions required certain level of knowledge and understanding about virtual agents.

## 4.1 Demographics

The demographic landscape of the respondents in the study presents (Table 4.1.1) a diverse cross-section of participants across various geographies and attributes. Of the 628 individuals who participated, the majority hail from India, comprising 57% of the total. This is followed by the United States, which accounts for 20%, while the Europe, Middle East, and Africa region and the Asia-Pacific region represent 10% and 13%, respectively. In terms of gender, the cohort skews significantly towards males, who constitute 81% of the respondents, with females representing a smaller fraction at 19%.

A closer look at the age distribution reveals a concentration of maturity and potential work experience in the bracket, with nearly half of the respondents, 48%, falling within the 30-40 year age range. The younger demographic, aged 18-30, comprises a modest 7.5%, whereas those between 40-50 years make up a substantial 39%. The eldest age group, those above 50 years, forms a mere 5.5% of the sample, indicating a tilt towards a younger demographic overall.

Considering the age of the firms the respondents are associated with, the data indicates a leaning towards newer entities; 75% of the firms are less than 20 years old. Contrastingly, the remaining quarter of the firms have been in operation for more than two decades, suggesting a mix of established and emerging business entities in the respondent pool.

When the lens shifts to technology adoption, the results show an overwhelming propensity towards rapid integration, with 95% of the respondents categorizing their adoption speed as 'Quick'. Only a minimal 5% consider their approach to be 'Deliberate', implying a significant emphasis on agility and responsiveness to technological advances within the surveyed group.

In the realm of R&D investment, there's a notable divide. A total of 39% of the respondents belong to firms that have high R&D investment, signalling a strong orientation towards innovation and development. However, a majority of 61% report low R&D investment, highlighting a possible gap between the recognition of R&D's importance and its actual implementation.

This demographic profile offers a glimpse into the varied characteristics of the respondents, with a predominant representation from India, a younger, predominantly male demographic, and a clear inclination towards swift technology adoption in relatively young firms. The dichotomy in R&D investment levels suggests diverse strategic priorities and the potential for nuanced insights into the adoption of virtual agents within the services sector.

**Table 4.1.1 – Demographic Profile of Respondents**

| Place | | Gender | | Age | | Firm Age | | Technology Adoption | | R&D Investment | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **India** | 360 (57) | **Male** | 507 (81) | **18-30 years** | 47 (7.5) | **Greater than 20 years** | 156 (25) | **Deliberate** | 27 (05) | **High** | 245 (39) |
| **US** | 126 (20) | **Female** | 121 (19) | **30-40 years** | 301 (48) | **Less than 20 years** | 472 (75) | **Quick** | 601 (95) | **Low** | 383 (61) |
| **EMEA** | 63 (10) | | | **40-50 years** | 245 (39) | | | | | | |
| **APAC** | 79 (13) | | | **Above 50 years** | 35 (5.5) | | | | | | |
| **Total** | **628 (100)** | **Total** | **628 (100)** | **Total** | **628 (100)** | **Total** | **628 (100)** | **Total** | **628 (100)** | **Total** | **628 (100)** |

***Source:*** *Primary Data*

***Note:*** The figures in parentheses are percentage to the total

## 4.2 PLS-SEM Results

### 4.2.1 Assessment of the Measurement Model

To assess the measurement models, Hair et. al (2019) guidelines on how to report PLS-SEM results has been followed. In this study, the individual indicator variables are reflective in nature and the assessment of reflective measurement models comprises of measuring the internal reliability, internal consistency, convergent validity and discriminant validity.

Internal reliability is ensured by looking into the indicator loadings, which are shown in Table 4.2.1.

**Table 4.2.1: Indicator Loadings**

| Construct | Item | Loading |
|---|---|---|
| **Performance Expectancy** | PE01 | 0.926 |
| | PE02 | 0.853 |
| | PE03 | 0.945 |
| | PE04 | 0.95 |
| **Effort Expectancy** | EE01 | 0.917 |
| | EE02 | 0.912 |
| | EE03 | 0.909 |
| **Facilitating Condition** | FC01 | 0.725 |
| | FC02 | 0.868 |

| | | |
|---|---|---|
| | FC03 | 0.853 |
| | FC04 | 0.798 |
| | FC05 | 0.769 |
| **Social Influence** | SI01 | 0.883 |
| | SI02 | 0.903 |
| | SI03 | 0.884 |
| **Perceived Severity** | PSE01 | 0.925 |
| | PSE02 | 0.912 |
| | PSE03 | 0.908 |
| **Perceived Susceptibility** | PS01 | 0.757 |
| | PS02 | 0.805 |
| | PS03 | 0.794 |
| | PS04 | 0.8 |
| **Perceived Threat** | PT01 | 0.832 |
| | PT02 | 0.824 |
| | PT03 | 0.825 |
| **Intention to Use** | IU01 | 0.936 |
| | IU02 | 0.88 |

| | | |
|---|---|---|
| | IU03 | 0.919 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

Indicator loadings explain the amount of variance shared between the individual variables and the construct associated with them. Indicator loadings ensures the indicator reliability of reflective measurement models. It can be seen in Table 4.2.1, that all the indicator loadings of our measurement models are more than the recommended critical value of 0.708 (Hair et. al, 2019). The critical value of 0.708 indicate that the associated construct explains more than 50% of the related indicator's variance and thus provide adequate item reliability. Thus, we can say that our model has satisfactory indicator reliability.

After ensuring indicator reliability, the next step is to assess internal consistency and convergent validity. The composite reliability and ρA is used to assess the internal consistency of reflective constructs, and AVE (Average Variance Extracted) is used to assess the covergent validity of reflective constructs. Compositae reliability, ρA and AVE of our assessment model is shown in Table 4.2.2.

It can be seen from Table 4.2.2, that both the composite reliability and ρA lies in between the recommended thresholds of 0.70 and 0.95. and all the AVE values exceed the recommended critical value of 0.5. Thus, we can say that our reflective assessment model has satisfactory level of internal consistence as well as convergent validity.

**Table 4.2.2: Reliability and Validity**

| Constructs | ρA | Composite Reliability | Average Variance Extracted |
|---|---|---|---|
| **Effort Expectancy** | 0.902 | 0.938 | 0.833 |
| **Facilitating Conditions** | 0.868 | 0.901 | 0.647 |
| **Intention to Use** | 0.901 | 0.937 | 0.831 |
| **Perceived Severity** | 0.907 | 0.939 | 0.838 |
| **Perceived Susceptibility** | 0.917 | 0.868 | 0.623 |
| **Perceived Threat** | 0.772 | 0.866 | 0.684 |
| **Performance Expectancy** | 0.941 | 0.956 | 0.845 |
| **Social Influence** | 0.891 | 0.920 | 0.792 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

The final step in the assessment of reflective measurement model is to ensure discriminant validity, which explains the extent to which each construct is empirically separate from other construct. HTMT (Heterotrait-monotrait) ratio is used to assess the discriminant validity of the model. The HTMT values are shown in Table 4.2.3.

HTMT is the mean correlation value of items across constructs in relation to the geometric mean of average correlations for item measuring the same construct. When HTMT values are high, discriminant validity is said to be low. It can be seen from Table 4.2.3., that all the HTMT values of our reflective measurement model are significantly lower than the conservative threshold limit of 0.85. Thus, it can be said that discriminant validity of our model is satisfactorily established.

**Table 4.2.3: Heterotrait-monotrait (HTMT) Ratio of Correlations**

| | Effort Expectancy | Facilitating Conditions | Intention to Use | Perceived Severity | Perceived Susceptibility | Perceived Threat | Performance Expectancy |
|---|---|---|---|---|---|---|---|
| **Facilitating Conditions** | 0.718 | | | | | | |
| **Intention to Use** | 0.485 | 0.564 | | | | | |
| **Perceived Severity** | 0.287 | 0.344 | 0.060 | | | | |
| **Perceived Susceptibility** | 0.262 | 0.299 | 0.278 | 0.723 | | | |
| **Perceived Threat** | 0.094 | 0.089 | 0.334 | 0.734 | 0.572 | | |
| **Performance Expectancy** | 0.547 | 0.623 | 0.475 | 0.426 | 0.276 | 0.147 | |
| **Social Influence** | 0.557 | 0.625 | 0.484 | 0.142 | 0.166 | 0.105 | 0.450 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

### 4.2.2 Assessment of the Structural Model

To assess the structural model, the guidelines of Hair et. al (2019) has been followed. According to Hair et. al (2019), assessment of the structural model involves three important things viz., checking the collinearity issues, checking the relevance and significance of path coefficients and checking the models' explanatory and predictive power. The results of our structural model were shown in Table 4.2.4 and the significance of the path coefficients with relevant hypothesis has been separately shown in Figure 4.2.1.

VIF (Variance Inflation Factor) is used to check collinearity issues in the model. It can be seen from Table 4.2.4, that the VIF values are close to 3. The largest inner VIF value of our model construct is 3.625 (Hair et. al, 2019). Thus, we can say that collinearity is not at critical level in the inner model and will not affect the regression results. Next, we examine path coefficients' size and significance.

Figure 4.2.1 illustrates the size and significance of path coefficients between the endogenous and exogenous constructs. It can be seen from figure 4.2.1 that perceived susceptibility ($\beta$ = 0.204) and perceived severity ($\beta$ = 0.481) has a significant positive correlation with the perceived threat. Further, performance expectancy (($\beta$ = 0.224), effort expectancy ($\beta$ = 0.135), facilitating condition ($\beta$ = 0.234), and social influence ($\beta$ = 0.124) are positively correlated and significant, whereas perceived threat ($\beta$ = -0.316) has a significant negative correlation with intention to use (endogenous construct).

A look into the $R^2$ values in Table 4.2.3 shows that perceived susceptibility and perceived severity are the important predictor constructs in explaining perceived threat ($R^2$ = 0.404); perceived threat, performance expectancy, effort expectancy, social influence and facilitating conditions are the important predictor constructs in explaining the intention to use (0.418). As the $R^2$ value of the endogenous construct is between 0.25 and 0.50, the model has achieved a moderate level of success (Hair et al., 2019) in explaining the intention to adopt virtual agents in the services sector.

***Accepted / Rejected Hypotheses***

1. **Performance Expectancy (H1):** Accepted, as performance expectancy has a significant positive influence on the adoption intention of virtual agents ($\beta = 0.224$).

2. **Effort Expectancy (H2):** Accepted, since effort expectancy significantly influences the adoption intention of virtual agents ($\beta = 0.135$).

3. **Social Influence (H3):** Accepted, with social influence having a significant positive impact on the adoption intention of virtual agents ($\beta = 0.124$).

4. **Facilitating Conditions (H4):** Accepted, as facilitating conditions are significantly related to the adoption intention of virtual agents ($\beta = 0.234$).

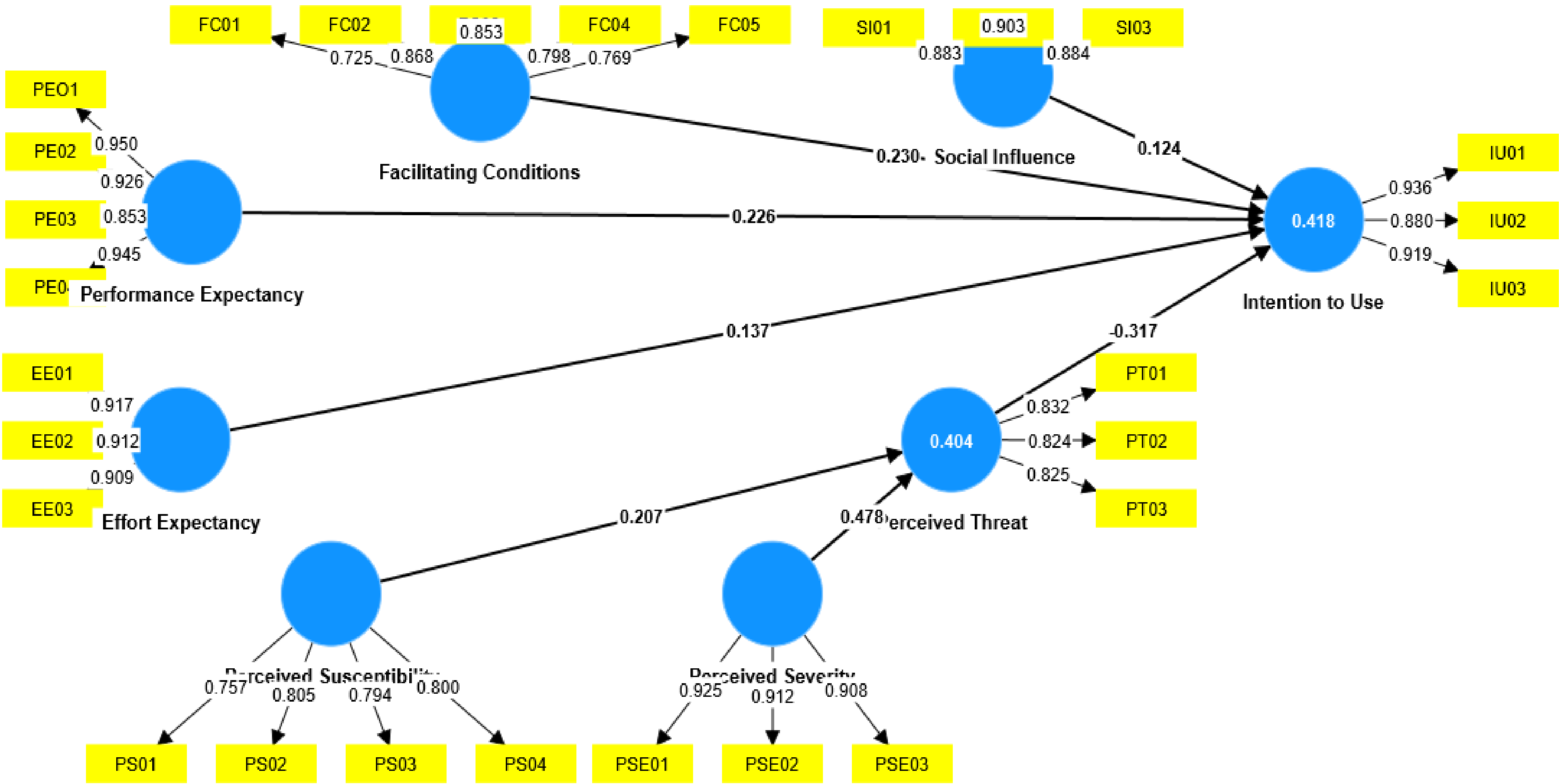
5. **Perceived Susceptibility (H5):** Accepted, given its significant positive correlation with perceived threat ($\beta = 0.204$).

6. **Perceived Severity (H6):** Accepted, as it significantly influences perceived threat ($\beta = 0.481$).

7. **Perceived Threat (H7):** Accepted, with perceived threat having a significant negative correlation with the adoption intention of virtual agents ($\beta = -0.316$).

The study's findings indicate a significant positive influence of performance expectancy on the intention to adopt virtual agents, as evidenced by a coefficient of 0.224, confirming the hypothesis that higher performance expectancy leads to greater adoption intention. Similarly, effort expectancy was found to significantly affect adoption intention, with a coefficient of 0.135, suggesting that the ease of use of virtual agents can positively drive their acceptance. Social influence also plays a crucial role, with its significant positive impact on adoption intention represented by a coefficient of 0.124, indicating that social norms and the influence of others are important factors in the decision to adopt virtual agents. Facilitating conditions were also significantly related to adoption intention, with a coefficient of 0.234, highlighting the importance of having the necessary resources and support to use virtual agents. In terms of health belief model constructs, perceived susceptibility showed a significant positive correlation with perceived threat (β = 0.204), suggesting that individuals' perceptions of their vulnerability to threats influence their perceived severity of these threats, which was also supported with a strong positive influence on perceived threat (β = 0.481). Interestingly, perceived threat was found to have a significant negative correlation with the adoption intention of virtual agents (β = -0.316), indicating that higher levels of perceived threat might deter individuals from adopting virtual agents.

**Figure 4.2.1: Structural Model Results**




***Source:*** *Primary Data*
***Note:*** PLS-SEM analysis is done using SMART PLS software

**Table 4.2.4: Structural Model Results**

| Outcome | R Sq. | Predictor | Direct Paths & Hypotheses | β | CI | Significance? | $f^2$ | VIF |
|---|---|---|---|---|---|---|---|---|
| **Performance Expectancy** | | CV | Firm Age -> Performance Expectancy | 0.055 | [-0.137; 0.248] | No | 0.007 | 3.625 |
| | | CV | R&D Investment -> Performance Expectancy | 0.015 | [-0.151; 0.182] | No | 0.024 | 2.659 |
| | | CV | Technology Adoption -> Performance Expectancy | -0.098 | [-0.436; 0.239] | No | 0.194 | 2.171 |
| **Effort Expectancy** | | CV | Firm Age -> Effort Expectancy | -0.041 | [-0.226; 0.146] | No | 0.004 | 3.625 |
| | | CV | R&D Investment -> Effort Expectancy | -0.138 | [-0.3; 0.025] | No | 0.014 | 2.659 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | CV | Technology Adoption -> Effort Expectancy | -0.036 | [-0.355; 0.271] | No | 0.027 | 2.171 |
| **Perceived Susceptibility** | CV | Firm Age -> Perceived Susceptibility | 0.112 | [-0.065; 0.278] | No | 0.003 | 3.625 |
| | CV | R&D Investment -> Perceived Susceptibility | 0.002 | [-0.173; 0.170] | No | 0.006 | 2.659 |
| | CV | Technology Adoption -> Perceived Susceptibility | 0.08 | [-0.282; 0.405] | No | 0.01 | 2.171 |
| **Perceived Severity** | CV | Firm Age -> Perceived Severity | -0.011 | [-0.199; 0.172] | No | 0 | 3.625 |
| | CV | R&D Investment -> Perceived Severity | 0.002 | [-0.173; 0.170] | No | 0.011 | 2.659 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | CV | Technology Adoption -> Perceived Severity | -0.076 | [-0.569; 0.365] | No | 0.005 | 2.171 |
| **Social Influence** | CV | Firm Age -> Social Influence | -0.079 | [-0.262; 0.105] | No | 0.009 | 3.625 |
| | CV | R&D Investment -> Social Influence | -0.179 | [-0.348; 0.103] | No | 0 | 2.659 |
| | CV | Technology Adoption -> Social Influence | 0.158 | [-0.111; 0.436] | No | 0.022 | 2.171 |
| **Facilitating Condition** | CV | Firm Age -> Facilitating Condition | -0.083 | [-0.277; 0.108] | No | 0 | 3.625 |
| | CV | R&D Investment -> Facilitating Condition | 0.021 | [-0.141; 0.181] | No | 0.006 | 2.659 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | CV | Technology Adoption -> Facilitating Condition | 0.147 | [-0.170; 0.463] | No | 0.041 | 2.171 |
| **Perceived Threat** | 0.404 | PS | Perceived Susceptibility -> Perceived Threat | 0.204 | [0.086; 0.334] | Yes | 0.04 | 1.024 |
| | | PSE | Perceived Severity -> Perceived Threat | 0.481 | [0.326; 0.616] | Yes | 0.211 | 1.06 |
| | | CV | Firm Age -> Perceived Threat | 0.126 | [-0.208; 0.447] | No | 0.014 | 3.635 |
| | | CV | R&D Investment -> Perceived Threat | -0.034 | [-0.155; 0.094] | No | 0.02 | 2.703 |
| | | CV | Technology Adoption -> Perceived Threat | 0.006 | [-0.261; 0.250] | No | 0.024 | 2.204 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Intention to Use** | 0.418 | PE | Performance Expectancy -> Intention to Use | 0.224 | [0.144; 0.304] | Yes | 0.055 | 1.412 |
| | | EE | Effort Expectancy -> Intention to Use | 0.135 | [0.052; 0.217] | Yes | 0.017 | 1.936 |
| | | SI | Social Influence -> Intention to Use | 0.124 | [0.029; 0.218] | Yes | 0.017 | 1.495 |
| | | FC | Facilitating Condition -> Intention to Use | 0.234 | [0.142; 0.325] | Yes | 0.042 | 1.423 |
| | | PT | Perceived Threat -> Intention to Use | -0.316 | [-0.390; -0.246] | Yes | 0.165 | 1.173 |
| | | CV | Firm Age -> Intention to Use | -0.014 | [-0.146; 0.123] | No | 0.001 | 3.794 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | CV | R&D Investment -> Intention to Use | -0.012 | [-0.137; 0.111] | No | 0.001 | 2.838 |
| | CV | Technology Adoption -> Intention to Use | -0.187 | [-0.504; 0.117] | No | 0 | 2.632 |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

CI = "95% bootstrap two-tailed confidence interval", CV = "Control Variable", PE = "Performance Expectancy", EE = "Effort Expectancy", FC = "Facilitating Conditions", SI = "Social Influence", PS = "Perceived Susceptibility", PSE = "Perceived Severity", PT = "Perceived Threat".

### 4.2.3 Mediation Analysis

The significance and strength of the mediating constructs have been assessed using bootstrapping procedure at a 95% confidence interval, and the results are shown in Table 4.2.5.

**Table 4.2.5: Structural Mediation**

| Path | β | CI | Significance? |
|---|---|---|---|
| Perceived Susceptibility -> Perceived Threat -> Intention to Use | -0.065 | [-0.116; -0.025] | Yes |
| Perceived Severity -> Perceived Threat -> Intention to Use | -0.152 | [-0.205; -0.099] | Yes |

***Source:*** *Primary Data*

***Note:*** *PLS-SEM analysis is done using SMART PLS software.*

It can be seen from the table, that perceived susceptibility (β = -0.065) and perceived severity (β = -0.152) have a significant larger negative influence on the intention via perceived threat.

### 4.2.4 Predictive Relevance of the Model

Table 4.2.4 indicates that the model has achieved moderate-to-high level of success (Hair et al., 2019) in explaining the adoption intention of virtual agents in the services sector, as the $R^2$ value of the endogenous construct (0.418) is more than 0.25. However, the $R^2$ statistics explains only the in-sample explanatory power of the model (Saari et. al, 2021). In order to assess the out-of-sample predict relevance of our model for cryptocurrency adoption, $Q^2$ values has been obtained for major constructs using blindfolding technique and the results are shown in Table 4.2.6.

**Table 4.2.6: Predict Relevance of the Model**

| **Construct** | **$Q^2$ Predict** |
|---|---|
| **Perceived Threat** | 0.125 |
| Intention to Use | 0.498 |

***Source:*** *Primary Data*

***Note:*** *PLS-SEM analysis is done using SMART PLS software*

It can be seen from Table 4.2.5, that the $Q^2_{predict}$ values are above zero. It could be noted that $Q^2_{predict}$ is used to verify that the predictions have outpaced the most naïve benchmark, which has been defined as “the indicator means from the analysis sample” (Hair et. al, 2019). This proves the out-of-sample predict relevance of the model.

### 4.2.5 Importance-Performance Map Analysis (IMPA)

In order to identify the impact and performance of the constructs with respect to the endogenous construct, importance-performance map analysis (IMPA) has been conducted with intention to use as the target construct and the results are shown in Table 4.2.7 and Figure 4.2.2. The results of IMPA demonstrate for which exogenous construct the total effects are important by explaining the variance of the endogenous construct (Saari et. al, 2021).

The Importance Performance Map Analysis on the adoption of virtual agents within the services sector presents intriguing insights. The data indicates that the ease of use of virtual agents, known as effort expectancy, has a positive and notably strong effect on their adoption, with a positive effect of 0.237 and a performance rating of 48.029. On the other hand, facilitating conditions seem to have a negligible positive impact, marked by an effect of 0.02 and a performance below the average at 45.908, suggesting they are not a significant determinant of adoption. Interestingly, the constructs of perceived severity and susceptibility show negative impacts on the intention to use virtual agents, accompanied by relatively low performance scores.

Moreover, perceived threat stands out with a considerable negative influence on adoption, showing an effect of -0.998. However, it scores high on performance at 51.005, signifying that while it is a prominent factor within the model, it acts as a substantial barrier to adoption, as individuals who perceive virtual agents as a threat are significantly less likely to employ them. Conversely, performance expectancy seems to have a minimal positive influence on adoption, with a low effect of 0.072 and a performance of 44.62, suggesting that the expectations of virtual agents' performance aren't a strong motivating factor for their use.

Social influence, however, with a moderate positive effect of 0.114 and a performance score of 46.138, suggests that social factors and peer influence are indeed relevant in the decision to adopt virtual agents. The 'Intention to Use' construct, with a performance of 49.859, serves as a comparative benchmark for the performance of other factors within the model. The average absolute effect size stands at 0.3, while the average performance score is 45.5, indicating that constructs exceeding this performance threshold are considered to be performing above average in the model.

In essence, the analysis suggests that while perceived threat is the most significant barrier to the adoption of virtual agents, effort expectancy and social influence are substantial positive drivers. The performance scores provide a measure of how well each construct explains the adoption, with perceived threat surprisingly registering the highest score despite its negative effect. Constructs falling below the average performance score may need to be reevaluated for their importance or might not be as vital in understanding the adoption behavior.

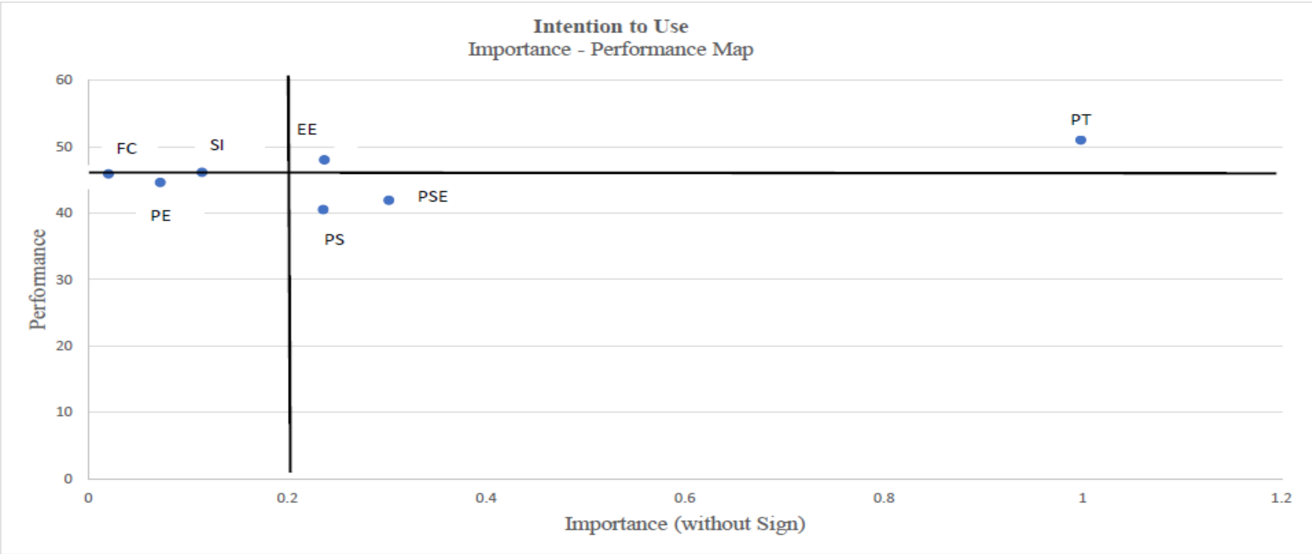
**Table 4.2.7: Importance-Performance Map Analysis**

| | Unstandardized Total Effect (With Sign) | Unstandardized Total Effect (Without Sign) | Performance | LV Performance |
|---|---|---|---|---|
| **Effort Expectancy** | 0.237 | 0.237 | 48.029 | - |
| **Facilitating Condition** | 0.02 | 0.02 | 45.908 | - |
| **Perceived Severity** | -0.302 | 0.302 | 41.938 | - |
| **Perceived Susceptibility** | -0.236 | 0.236 | 40.546 | - |
| **Perceived Threat** | -0.998 | 0.998 | 51.005 | - |
| **Performance Expectancy** | 0.072 | 0.072 | 44.62 | - |
| **Social Influence** | 0.114 | 0.114 | 46.138 | - |
| **Intention to Use** | - | - | - | 49.859 |
| **Average** | - | 0.3 | 45.5 | |

***Source:*** *Primary Data*

***Note:*** PLS-SEM analysis is done using SMART PLS software

**Figure: 4.2.2: Importance-Performance Map Analysis**




***Note:*** *PE = Performance Expectancy, EE = Effort Expectancy, FC = Facilitating Conditions, SI = Social Influence, PS = Perceived Susceptibility, PSE = Perceived Severity, PT = Perceived Threat.*

# Chapter V – Discussion

## 5.1 Major Findings

The major findings from the study on the factors affecting the adoption of virtual agents in the services sector, as per the presented results, are as follows:

- **Major Predictors:** Perceived susceptibility ($\beta = 0.204$) and perceived severity ($\beta = 0.481$) show a significant positive correlation with perceived threat. Performance expectancy ($\beta = 0.224$), effort expectancy ($\beta = 0.135$), facilitating condition ($\beta = 0.234$), and social influence ($\beta = 0.124$) are positively correlated and significant. Perceived threat is significantly negatively correlated ($\beta = -0.316$) with the intention to use virtual agents.
- **Explanatory and Predictive Power:** The model's $R^2$ values indicate a moderate level of success in explaining the intention to adopt virtual agents in the services sector. Perceived susceptibility and severity are key predictors for perceived threat ($R^2 = 0.404$). Perceived threat, along with performance expectancy, effort expectancy, social influence, and facilitating conditions, are significant predictors for the intention to use virtual agents ($R^2 = 0.418$).
- **Mediation Analysis**: Perceived susceptibility ($\beta = -0.065$) and perceived severity ($\beta = -0.152$) have a significant negative influence on the intention to use virtual agents, mediated by perceived threat.
- **Importance-Performance Map Analysis:** Effort expectancy has a strong positive effect (effect of 0.237) and high performance (48.029) on adoption, indicating it's a significant driver. Facilitating conditions have a negligible positive impact and below-average performance (45.908), suggesting they are less influential. Perceived severity and susceptibility negatively impact the intention to use virtual agents and show

relatively low performance scores. Perceived threat has a considerable negative influence (effect of -0.998) but a high-performance score (51.005), indicating it's a significant barrier to adoption.

- Performance expectancy has a minimal positive influence with a low effect (0.072) and performance (44.62). Social influence has a moderate positive effect (0.114) and a performance score of 46.138, signifying its relevance in the adoption decision. The average absolute effect size is 0.3, and the average performance score is 45.5, serving as a benchmark for evaluating the constructs.

In summary, the study reveals that while perceived threat is a major barrier to the adoption of virtual agents, factors like effort expectancy and social influence play significant roles in driving adoption. The analysis also points out that some constructs, though present, may not be as critical in understanding the adoption behavior in the services sector.

## 5.2 Perceived Threat in the Adoption of Virtual Agents

The adoption of virtual agents in the services sector presents various challenges and perceived threats that require careful consideration and mitigation strategies. These concerns have been studied in different contexts, shedding light on the potential risks associated with the implementation of virtual agents. In the context of healthcare e-commerce, Deventer and Zidda (2023) have explored the adoption of virtual agents. They emphasize the importance of a perceived value perspective, suggesting that organizations must not only focus on the advantages but also address the perceived threats that may arise from the use of virtual agents in healthcare-related services. This includes concerns related to data privacy, trust, and the impact on human healthcare providers.

Another dimension of perceived threats relates to customer attitudes and acceptance of service robots in the hospitality industry. Huang et al. (2021) discuss the effects of perceived identity threat and realistic threat on customers' negative attitudes and usage intentions toward hotel service robots. Their findings highlight the importance of anthropomorphism in moderating these threats and shaping customer perceptions.

In the banking industry, Hasan et al. (2023) examine the adoption of conversational assistants and the role of perceived risk as a moderator. They suggest that perceived risk factors need to be addressed to facilitate the acceptance of virtual agents in banking services, including concerns related to security and reliability.

The adoption of virtual communication tools in the educational sector is also subject to scrutiny. Gupta and Mathur (2023) discuss the adoption of virtual communication by educational leaders and emphasize the moderating role of perceived risk and benefits. They highlight those concerns about technology adoption, such as data security and effectiveness, must be balanced against the perceived benefits of virtual communication.

In the realm of service encounters and customer acceptance, Fernandes and Oliveira (2021) investigate the drivers of digital voice assistants' adoption. They underscore the importance of understanding consumers' acceptance of automated technologies and the factors that influence their willingness to interact with virtual agents in various service settings. Physician acceptance of information technologies in healthcare is explored by Walter and Lopez (2008). They emphasize the role of perceived threat to professional autonomy, suggesting that healthcare professionals may be resistant to technology adoption if they perceive it as a threat to their professional roles and decision-making authority.

In the context of cloud technology adoption, Ho et al. (2017) examine the causal effects of perceived risk and subjective norms. They highlight that trust and perceived risk play significant roles in shaping organizations' decisions to adopt cloud technologies, emphasizing the importance of managing perceived threats in the technology adoption process.

The adoption of virtual healthcare services, particularly electronic government telemedicine services, is examined by Upadhyay, Kamble, and Navare (2023) in the context of the Indian healthcare sector. They investigate how healthcare consumers perceive and adopt virtual healthcare services, considering factors such as accessibility, convenience, and trust. Lastly, Itani and Hollebeek (2021) explore visitors' behavioral intentions concerning virtual reality attraction site tours during and post-COVID-19. While not directly related to the services sector, their research underscores the changing dynamics of virtual experiences and how individuals' intentions may shift in response to external factors.

The adoption of virtual agents in the services sector is a multifaceted issue with various perceived threats and challenges. These concerns range from job displacement and technology limitations to privacy, ethics, and user acceptance. Researchers across different domains have investigated these issues, providing insights into the complex landscape of virtual agent adoption and the need for comprehensive strategies to address perceived threats while harnessing the benefits of this technology. While the adoption of virtual agents in the services sector offers numerous benefits, including improved efficiency and cost savings, it also poses several perceived threats. These threats encompass job displacement, technological limitations, privacy and security concerns, ethical considerations, overreliance on technology, user acceptance issues, and regulatory and legal challenges. Addressing these concerns through thoughtful strategies, transparency, responsible data use, and a balanced approach is essential for successful integration of virtual agents into the services sector.

Overcoming the perceived threats associated with the adoption of virtual agents in the services sector requires a comprehensive approach that takes into account various aspects of these challenges. To address concerns about job displacement, organizations should focus on reskilling and upskilling their workforce. Training programs can equip employees with the skills required to complement virtual agent capabilities, ensuring a smooth transition while retaining valuable human talent.

Mitigating technology limitations can be achieved through the implementation of hybrid models that combine the strengths of both humans and virtual agents. This approach allows virtual agents to handle routine tasks efficiently, while humans step in for complex or emotionally charged interactions. Privacy and data security concerns should be addressed through robust data protection measures, including data encryption and strict data governance policies. Organizations must comply with relevant data protection regulations and maintain transparent communication with users about data usage.

Ethical considerations can be managed by ensuring transparency in virtual agent interactions. Clear disclosure of virtual agents' non-human identity and communication regarding their capabilities and limitations build trust. Ethical AI development practices should also be adopted to prevent biases in responses. Balancing technology dependence is crucial to prevent overreliance on virtual agents. Human oversight in critical service areas and offering customers the choice between human and virtual agent interactions provide a balanced approach. To mitigate technological dependence, organizations should develop backup and redundancy plans to handle technical failures or system outages. Alternative methods for customers to access services during downtime should be readily available.

Closing the skills gap requires investing in employee training to prepare the workforce to collaborate effectively with virtual agents. Encouraging continuous learning and adaptation to technological changes is essential. Enhancing user acceptance involves prioritizing user-centric design, gathering feedback, and making iterative improvements based on user preferences and needs. Educating customers about the benefits of virtual agents and addressing common concerns through clear communication can boost user acceptance. Navigating regulatory and legal challenges requires the establishment of dedicated compliance teams to ensure adherence to industry-specific regulations and standards. Staying informed about evolving regulations and adapting virtual agent systems accordingly is essential for maintaining compliance.

By adopting these comprehensive strategies, organizations can effectively overcome the perceived threats associated with the adoption of virtual agents. This approach allows businesses to harness the efficiency and customer service improvements offered by virtual agents while ensuring ethical practices, data security, and customer trust are maintained.

**5.3 Performance Expectancy**

Performance expectancy plays a pivotal role in the adoption of virtual service agents in the services sector, as highlighted by various studies in the field (Nye & Silverman, 2013; Ling et al., 2021; Priya & Sharma, 2023; Alanzi et al., 2023; Wutz et al., 2023; Deventer & Zidda, 2023). It refers to users' perceptions of how using virtual agents can help them achieve their goals and enhance their overall performance in service interactions.

Users in the services sector anticipate that virtual agents will significantly improve efficiency and speed in service delivery (Ling et al., 2021). Virtual agents are expected to handle routine tasks and inquiries swiftly and accurately, reducing the time and effort users need to invest in interacting with service providers (Alanzi et al., 2023). The 24/7 availability of virtual agents is another aspect contributing to performance expectancy (Deventer & Zidda, 2023). Users value the uninterrupted access to assistance or information, aligning with their expectation of prompt and convenient service (Ling et al., 2021).

Consistency and accuracy are also vital components of performance expectancy (Wutz et al., 2023). Virtual agents are perceived to consistently provide accurate and up-to-date information, instilling confidence in users regarding the reliability and performance of the technology (Alanzi et al., 2023). Personalization and customization capabilities enhance performance expectancy by tailoring interactions based on user data and preferences (Priya & Sharma, 2023). Users appreciate virtual agents that understand their needs and provide relevant solutions, aligning with their expectations of improved performance.

Virtual agents excel in handling repetitive tasks, and users recognize their efficiency in automating such activities (Wutz et al., 2023). This perception that virtual agents can handle routine work effectively positively influences overall performance expectations. Moreover, users associate the use of virtual agents with a reduction in human error, further contributing to performance expectancy (Nye & Silverman, 2013). Virtual agents follow predefined algorithms and rules, making them less susceptible to mistakes in tasks like data entry or calculations, aligning with users' expectations of reliability and accuracy.

The enhanced customer experience offered by virtual agents, through quick and consistent service, prompt issue resolution, and personalized recommendations, aligns with users' expectations of a seamless and efficient interaction, thus boosting performance expectancy (Deventer & Zidda, 2023). Additionally, users often consider cost savings associated with virtual agent adoption (Priya & Sharma, 2023). When organizations can pass on the benefits of cost-effective operations to users, it aligns with their expectations of improved performance. Finally, feedback mechanisms and continuous improvement in virtual agent capabilities reinforce users' positive perceptions of performance expectancy (Wutz et al., 2023). Users appreciate when their input contributes to enhancing virtual agents' performance and overall utility.

Performance expectancy is a crucial factor influencing the adoption of virtual service agents in the services sector. Users' perceptions of improved efficiency, 24/7 availability, consistency, personalization, reduced human error, enhanced customer experience, cost savings, and the potential for feedback-driven improvements collectively shape their expectations of how virtual agents can positively impact their service interactions. Meeting or exceeding these expectations is vital for successful adoption and user acceptance of virtual service agents.

### 5.4 Effort Expectancy

Effort expectancy is a crucial determinant in the adoption of virtual agents within the services sector, a fact underscored by several studies in the field (E Norberg et al., 2023; Esposito et al., 2021; Zojaji et al., 2020; Adegoke et al., 2022; Nashold Jr, 2020; Yoo et al., 2016; Lacity et al., 2017; Song, 2019). Users expect virtual agents to offer a user-friendly experience, characterized by intuitive interfaces that are easy to navigate (Esposito et al., 2021). Complex or confusing interfaces can deter users, as they perceive a higher level of effort required to engage with the technology. Furthermore, the simplicity of interaction is paramount, with users anticipating that virtual agents will streamline processes and reduce the steps required to complete tasks or access information (Yoo et al., 2016). In the services sector, where efficient service delivery is crucial, users value virtual agents that expedite task execution and minimize complexity (E Norberg et al., 2023).

Effort expectancy also extends to accessibility and multichannel support (Adegoke et al., 2022). Users expect virtual agents to be readily available across various communication channels, aligning with their preference and reducing the effort required to engage with the technology. For instance, a virtual agent accessible through a mobile app or a website enhances user convenience. Moreover, the integration of natural language processing capabilities into virtual agents significantly impacts effort expectancy (Nashold Jr, 2020). Users appreciate when virtual agents can understand and respond to natural language queries, as it eliminates the need to learn specific commands or technical jargon, simplifying interaction.

Effort expectancy is also influenced by the efficient execution of tasks by virtual agents, reducing the perceived effort required for users (Zojaji et al., 2020). Users value virtual agents that complete tasks quickly and accurately, enhancing their overall experience and encouraging adoption. Guidance and assistance mechanisms within virtual agents play a pivotal role in reducing user effort (Lacity et al., 2017). Clear instructions, tooltips, and contextual help ensure that users feel supported and guided throughout their interactions, reducing confusion and frustration. Furthermore, users associate effort expectancy with effective error handling (Song, 2019). When virtual agents provide user-friendly error messages and prompts that guide users in resolving issues, it reduces the perceived effort and contributes to a smoother user experience.

Personalization and context awareness in virtual agents are also essential for reducing effort (E Norberg et al., 2023). Users appreciate when virtual agents remember previous interactions and provide tailored responses, reducing the effort required to reiterate information or preferences. Effort expectancy plays a crucial role in the adoption of virtual agents in the services sector. Users expect these technologies to be user-friendly, simplify interaction, be accessible across channels, incorporate natural language processing, execute tasks efficiently, provide guidance, handle errors effectively, and offer personalization. Aligning virtual agents with these expectations enhances the ease of use, reduces perceived effort, and encourages user adoption within the services sector.

## 5.5 Social Influence

Social influence exerts a substantial impact on the adoption of virtual agents in the services sector, as evident in various studies. Norberg, Nettelbladt, and Nilsson (2023) investigate how stereotypes affect social agent interaction and patterns of adoption. Stereotypes can shape individuals' attitudes and behaviors, potentially influencing their willingness to interact with virtual agents based on preconceived notions. Moreover, Esposito et al. (2021) delve into the attitudes of elder users toward assistive virtual agents, highlighting the role of voice and gender in shaping perceptions. Elder users may be influenced by their peers' experiences and opinions, which can either encourage or hinder adoption.

The politeness behaviors exhibited by virtual agents also play a role in social influence. Zojaji, Peters, and Pelachaud (2020) examine how virtual agent politeness behaviors impact users' decisions to join conversational groups. Politeness cues can foster a sense of comfort and trust, making users more likely to engage with virtual agents and adopt them for collaborative tasks in the services sector.

In the context of real estate agency practice, Adegoke et al. (2022) analyze the criteria for measuring determinants of virtual reality technology adoption. Their research underscores the importance of social influence within professional networks, as real estate agents may be swayed by the adoption behaviors and recommendations of their peers when considering the integration of virtual reality tools into their practices.

Trust, a critical component of social influence, is explored by Nashold Jr. (2020) in the context of consumer adoption of artificial intelligence-driven virtual finance assistants. Trust in the technology and the recommendations of influential sources can significantly impact individuals' decisions to adopt virtual finance assistants for managing their financial affairs.

Furthermore, human likeness, as discussed by Yoo, Kwon, and Lee (2016), can affect the adoption of robot-assisted learning systems. When virtual agents exhibit human-like characteristics, users may be more inclined to engage with them for educational purposes, driven by the social influence of perceiving the agents as relatable and approachable. Social influence shapes the adoption of virtual agents in the services sector through a range of factors, including stereotypes, attitudes, politeness behaviors, recommendations from peers, trust, and perceptions of human likeness. Understanding and leveraging these influences can be essential for organizations and technology providers seeking to promote the adoption of virtual agents and integrate them effectively into service delivery processes.

## 5.6 Facilitating Conditions

Facilitating conditions are pivotal in shaping the successful adoption of virtual agents in the service sector. In the banking industry, the case of SEB Bank, as discussed by Lacity, Willcocks, and Craig (2017), exemplifies the importance of technological infrastructure and resource allocation. SEB Bank's cognitive virtual agents required a robust technological foundation and dedicated resources to function effectively, highlighting how these facilitating conditions can enable seamless integration.

User acceptance is a critical aspect of virtual agent adoption, as explored in Song's doctoral dissertation (2019). Facilitating conditions, in this context, encompass user education and training. Providing users with clear instructions and support materials can help users navigate and interact with virtual agents, fostering greater acceptance and usage.

The adoption of virtual agents also hinges on compliance with legal and regulatory standards. In the healthcare e-commerce domain, Deventer and Zidda (2023) emphasize the need for facilitating conditions related to legal compliance and data management. Ensuring adherence to data privacy regulations and establishing the necessary legal frameworks are crucial facilitating conditions to build trust with users. Moreover, Huang et al. (2021) highlight the significance of facilitating conditions related to perceived identity threat and realistic threat. Organizations must address these threats to mitigate negative attitudes and enhance usage intentions. Facilitating conditions may involve anthropomorphizing virtual agents to reduce perceived threats and increase user comfort.

In the educational sector, Gupta and Mathur's study (2023) underscores the moderating role of perceived risk and benefits in virtual communication adoption by educational leaders. Facilitating conditions here encompass strategies to manage and mitigate perceived risks, enabling educational leaders to make informed decisions about the adoption of virtual communication tools.

In the context of service encounters, Fernandes and Oliveira (2021) delve into the drivers of digital voice assistant adoption. Facilitating conditions extend to performance metrics and evaluation, as organizations need to continuously assess and improve virtual agents based on user feedback and data analysis. Additionally, Walter and Lopez (2008) highlight the role of perceived threat to professional autonomy in physician acceptance of information technologies. Facilitating conditions may involve strategies to address these threats, ensuring that healthcare professionals perceive technology adoption as an enhancement rather than a detriment to their roles.

Trust and perceived risk are central to technology adoption, as explored by Ho et al. (2017) in the context of cloud technology adoption. Establishing trust among users and managing perceived risks are facilitating conditions that can accelerate the adoption of virtual agents, especially in industries where data security is paramount. Finally, Upadhyay, Kamble, and Navare's research (2023) on Indian healthcare consumers' adoption of electronic government telemedicine service underscores the need for facilitating conditions to support virtual healthcare adoption. These conditions may involve resource allocation, technical support, and user education to ensure a smooth transition to virtual healthcare services.

Facilitating conditions encompass a wide array of factors, including technological infrastructure, integration, legal compliance, user education, performance evaluation, and addressing perceived threats and risks. These conditions are essential for organizations aiming to successfully integrate virtual agents into the service sector and maximize their benefits while mitigating potential challenges.

### 5.7 Managerial Implications

The study results on the adoption of virtual agents in the service sector offer several managerial implications that can guide decision-making and strategic planning in organizations. Understanding these implications is crucial for effectively integrating virtual agents into service offerings. Here are the key managerial implications derived from the study:

- ***Addressing Perceived Threats:*** The significant negative impact of perceived threats on the intention to use virtual agents suggests that managers need to actively address and mitigate these concerns. This could involve clear communication about the security, privacy, and accuracy of virtual agents. Educating customers about the benefits and safeguards associated with virtual agents can help reduce perceived threats.
- ***Emphasizing Ease of Use:*** The strong positive effect of effort expectancy indicates that virtual agents should be user-friendly and easy to navigate. Managers should focus on simplifying the user interface and ensuring that virtual agents are intuitive and require minimal effort to interact with. This will likely increase customer satisfaction and adoption rates.
- ***Facilitating Conditions:*** Despite their negligible impact, facilitating conditions should not be ignored. Managers should ensure that the necessary technical and

infrastructural support is in place for the effective use of virtual agents. This includes reliable internet access, compatibility with various devices, and technical support.

- ***Leveraging Social Influence:*** The positive correlation between social influence and the intention to use virtual agents implies that managers can benefit from marketing strategies that leverage social proof. This could involve showcasing testimonials, case studies, or endorsements from satisfied users or influential figures.
- ***Managing Expectations:*** Since performance expectancy has a minimal positive influence, it's important for managers to set realistic expectations about the capabilities of virtual agents. Overpromising on performance can lead to dissatisfaction and reduced trust in the technology.
- ***Targeting Key Predictors:*** Perceived susceptibility and severity are key predictors for perceived threat, and thus, addressing these factors can directly impact the overall adoption of virtual agents. Managers should focus on strategies that reduce perceived risks associated with virtual agents and emphasize their benefits in handling service tasks effectively.
- ***Continuous Improvement Based on Feedback:*** The varying performance scores of different constructs suggest the need for continuous monitoring and improvement. Managers should gather and analyze customer feedback to understand which aspects of virtual agents are well-received and which need enhancements.
- ***Educational Initiatives:*** Given the negative impacts of perceived severity and susceptibility, educational initiatives that inform customers about the functionality, security, and benefits of virtual agents can be beneficial. This could involve online tutorials, FAQs, and informative content that demystifies the technology.
- ***Strategic Positioning and Marketing:*** The findings should inform how virtual agents are positioned in the market. Highlighting their ease of use, efficiency, and reliability

in marketing communications can attract more users. Also, addressing common misconceptions and fears through marketing can help in reducing perceived threats.

- ***Investing in Technology and Innovation:*** To stay competitive and ensure that virtual agents meet the evolving needs of customers, continuous investment in technological advancements is essential. This includes incorporating AI advancements, improving natural language processing capabilities, and ensuring seamless integration with existing systems.

The managerial implications of the study emphasize a balanced approach that focuses on reducing perceived barriers, enhancing the ease of use, leveraging social influence, managing customer expectations, and continuously improving the technology based on user feedback. These strategies can help organizations in successfully integrating virtual agents into their service offerings and maximizing their adoption and effectiveness.

# Chapter VI – Conclusion

## 6.1 Study Implications

Based on the structural model results of the study on the adoption of virtual agents in the services sector, several key implications can be drawn:

- **Perceived Threat as a Major Barrier**: The negative correlation of perceived threat with the intention to use virtual agents ($-\beta = 0.316$) and its high performance score (51.005) in the IMPA suggest that perceived threat is a significant barrier to adoption. This implies the need for strategies to mitigate these perceived threats, such as ensuring data privacy, security, and addressing user concerns about the reliability of virtual agents.

- **Importance of Perceived Susceptibility and Severity**: These constructs have been identified as important predictors of perceived threat ($R^2 = 0.404$) and have a significant negative influence on the intention to use virtual agents when mediated by perceived threat. This underscores the need for managing public perceptions about the risks associated with virtual agents.

- **Effect of Effort Expectancy**: The strong positive effect of effort expectancy ($\beta = 0.237$) on adoption and its relatively high performance rating (48.029) highlight the importance of user experience in the design of virtual agents. Making virtual agents easy to use and understand can significantly influence their adoption.

- **Lesser Impact of Facilitating Conditions**: Given its negligible positive impact (effect of 0.02) and below-average performance score (45.908), it appears that facilitating conditions are not key determinants of virtual agent adoption. This suggests that while necessary, merely providing supportive conditions may not be enough to drive adoption.

- **Role of Social Influence**: With a moderate positive effect ($\beta = 0.114$) and a performance score of 46.138, social influence is a relevant factor. This implies that adoption can be influenced by social trends, peer recommendations, and the perceived popularity of virtual agents.

- **Minimal Influence of Performance Expectancy**: The low effect (0.072) and performance (44.62) of performance expectancy suggest that expectations regarding the performance of virtual agents are not major motivators for their use. This could mean that users are more concerned with other aspects like usability or security than just performance.

- **Negative Impact of Perceived Severity and Susceptibility**: These constructs not only influence perceived threat but also have a direct negative impact on the intention to use virtual agents. Addressing misconceptions and educating users about the actual risks and benefits of virtual agents could be beneficial.

- **Moderate Success of the Model**: The $R^2$ value of the endogenous construct (0.418) indicates that the model has achieved a moderate level of success in explaining the intention to adopt virtual agents. This suggests there may be other factors influencing adoption that are not captured in the model.

- **Re-evaluation of Constructs with Low Performance**: Constructs that fall below the average performance score in the IMPA may need to be reassessed for their importance or relevance in the context of virtual agent adoption.

- **Strategic Focus on Positive Drivers**: Given that effort expectancy and social influence are substantial positive drivers, focusing on these aspects can be a strategic approach to enhance the adoption of virtual agents.

In summary, these implications provide valuable insights for both the development and marketing strategies for virtual agents in the service sector, highlighting the importance of addressing perceived threats, enhancing usability, and leveraging social influences.

### 6.2 Study Recommendations

Based on the findings and implications of our study on the adoption of virtual agents in the services sector, we propose the following recommendations to guide practitioners, developers, and policymakers in this domain:

- **Mitigating Perceived Threats**: Given the significant impact of perceived threats on adoption, it is essential to develop strategies to alleviate these concerns. This includes ensuring robust privacy and security measures, transparent communication about how virtual agents operate, and addressing common misconceptions about their functionality.

- **Enhancing User Experience**: Since effort expectancy is a key positive driver for adoption, virtual agents should be designed with a focus on user-friendliness. Simplifying the interaction process, providing intuitive interfaces, and ensuring virtual agents are easily navigable can enhance user experience and encourage adoption.

- **Leveraging Social Influence**: Implement marketing and communication strategies that utilize social proof and peer influence. Showcasing success stories, user testimonials, and endorsements from trusted sources can effectively increase adoption rates by influencing potential users' perceptions positively.

- **Educational Initiatives**: Given the negative impact of perceived severity and susceptibility, educational initiatives are crucial. These should aim at informing potential users about the practical benefits, reliability, and safety of virtual agents, dispelling myths and clarifying any misconceptions.
- **Revisiting Facilitating Conditions**: While the impact of facilitating conditions is minimal, ensuring that the basic infrastructural and technical requirements are met remains essential. This includes providing reliable internet connectivity, compatible hardware, and user support.
- **Performance Expectancy Reevaluation**: The minimal influence of performance expectancy suggests a need to reassess user expectations. Focus on communicating the realistic capabilities of virtual agents and manage user expectations to align with what the technology can deliver.
- **Targeted Messaging**: Tailor communication and marketing messages to address specific concerns and highlight the benefits most relevant to the target audience. This involves understanding the unique needs and preferences of different user segments.
- **Continuous Improvement and Feedback Integration**: Establish mechanisms for continuous feedback collection and analysis. Use this data to make iterative improvements in virtual agent technology, focusing on areas that users find most valuable or in need of enhancement.

- **Policy and Regulation Advocacy**: Engage with policymakers to advocate for regulations and standards that support the ethical and secure use of virtual agents. This can help in building public trust and smoothing the path for broader adoption.

- **Strategic Partnerships and Collaborations**: Form partnerships with technology developers, service providers, and academic institutions to stay at the forefront of virtual agent technology. Collaborations can lead to innovations that address current limitations and expand the capabilities of virtual agents.

- **Diversified Use Cases Exploration**: Explore and demonstrate varied use cases of virtual agents across different sectors of the service industry. Showcasing the versatility of virtual agents can attract a broader range of users.

- **Long-Term Adoption Strategies**: Develop long-term strategies focusing on the gradual integration of virtual agents into service operations. This includes planning for scalability, updating training programs, and preparing the workforce for technology adoption.

By implementing these recommendations, stakeholders in the services sector can better navigate the challenges and opportunities associated with the adoption of virtual agents, leading to more effective and widespread use of this transformative technology.

### 6.3 Conclusion

This study has provided comprehensive insights into the factors influencing the adoption of virtual agents in the services sector. Through a detailed analysis of structural model results, including assessments of collinearity, path coefficients, mediation effects, and Importance-Performance Map Analysis (IMPA), we have gained a nuanced understanding of the dynamics at play in the adoption process.

Key findings indicate that perceived threat poses a significant barrier to adoption, while factors such as effort expectancy and social influence emerge as crucial drivers. The study reveals the complex interplay of various constructs like perceived susceptibility, perceived severity, performance expectancy, and facilitating conditions in shaping user attitudes and intentions towards virtual agents.

One of the most striking revelations is the dichotomy between the perceived threat and its actual impact on adoption. Despite being a deterrent, perceived threat also registers high in performance, indicating its prominence in users' decision-making processes. This paradox underscores the need for targeted strategies to mitigate perceived threats and alter negative perceptions.

The study's recommendations provide a roadmap for practitioners, developers, and policymakers. They highlight the importance of enhancing user experience, leveraging social influence, addressing security and privacy concerns, and engaging in continuous improvement and feedback integration. Educational initiatives and strategic marketing are also crucial in changing the narrative around virtual agents and fostering a more receptive environment for their adoption.

In conclusion, the adoption of virtual agents in the services sector is a multifaceted issue, influenced by a combination of technological, psychological, and social factors. The findings of this study offer valuable insights for shaping the future development and integration of virtual agents, emphasizing the need for a balanced approach that addresses both the technological capabilities of these agents and the perceptions and attitudes of their potential users. As we move forward, it is imperative to continuously adapt and evolve these strategies in line with emerging trends and user feedback, ensuring that virtual agents can fully realize their potential as transformative tools in the services sector.

## BIBLIOGRAPHY

Adam, M., Toutaoui, J., Pfeuffer, N., & Hinz, O., 2019. Investment decisions with robo-advisors: The role of anthropomorphism and personalized anchors in recommendations. In: Proceedings of the 27th European Conference on Information Systems (ECIS). Sweden: Stockholm & Uppsala.

Adam, M., Wessel, M., & Benlian, A., 2021. AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets, 31*(2), pp.427–445.

Adegoke, A. S., Oladokun, T. T., Ayodele, T. O., Agbato, S. E., Jinadu, A. D., & Olaleye, S. O., 2022. Analysing the criteria for measuring the determinants of virtual reality technology adoption in real estate agency practice in Lagos: a DEMATEL method. *Property Management, 40*(3), pp.285-301.

Agarwal, R., & Prasad, J., 1998. A conceptual and operational definition of personal innovativeness in the domain of information technology. *Information Systems Research, 9*(2), pp.204–215.

Aggarwal, P., Vaidyanathan, R., & Rochford, L., 2007. The wretched refuse of a teeming shore? A critical examination of the quality of undergraduate marketing students. *Journal of Marketing Education, 29*(3), pp.223–233.

Agrawal, A., Gans, J.S. and Goldfarb, A., 2018. Human judgment and ai pricing. *AEA Papers and Proceedings, 23*(10), pp.58-63.

Alanzi, T., Almahdi, R., Alghanim, D., Almusmili, L., Saleh, A., Alanazi, S., ... & ALBLWI, A., 2023. Factors Affecting the Adoption of Artificial Intelligence-Enabled Virtual Assistants for Leukemia Self-Management. *Cureus*, *15*(11), pp.418-426.

Alnawas, I., & Aburub, F., 2016. The effect of benefits generated from interacting with branded mobile apps on consumer satisfaction and purchase intentions. *Journal of Retailing and Consumer Services, 3*(1), pp.313–322.

Alshurideh, M., 2014a. The Factors Predicting Students' Satisfaction with Universities' Healthcare Clinics' Services: A Case-Study from the Jordanian Higher Education Sector. *Dirasat: Administrative Sciences*. *41*(2), pp.451-464.

Alshurideh, M., 2014b. A Qualitative Analysis of Customer Repeat Purchase Behaviour in the UK Mobile Phone Market. *Journal of Management Research, 6*(1), pp.109-125.

Alshurideh, M., Shaltoni, A-M., & Hijawi, D., 2014. Marketing Communications Role in Shaping Consumer Awareness of Cause-Related Marketing Campaigns. *International Journal of Marketing Studies, 6*(2), pp.163- 168.

Altamony, H., Masa'deh, R., Alshurideh, M., &Obeidat, B., 2012. Information systems for competitive advantage: Implementation of an organisational strategic management process. Proceedings of the 18th IBIMA conference on Innovation and Sustainable Economics Competitive advantage: From Development to World Economies. International Business Information Management Association.

Ameen, N., Tarhini, A., Reppel, A., & Anand, A., 2021. Customer experiences in the age of artificial intelligence. *Computers in Human Behavior, 114*(106548), p.106548.

Amorese, T., Greco, C., Cuciniello, M., Buono, C., Palmero, C., Buch-Cardona, P., Escalera, S., Torres, M.I., Cordasco, G. & Esposito, A., 2022. Using Eye Tracking to Investigate Interaction between Humans and Virtual Agents. Proceedings - 2022 IEEE International Conference on Cognitive and Computational Aspects of Situation Management, *CogSIMA 2022*, pp.125.

Anbananthen, K.S.M., Kannan, S., Busst, M.M.A., Muthaiyah, S. & Lurudusamy, S.N., 2022. Typographic Error Identification and Correction in Chatbot Using N-gram Overlapping Approach. *Journal of System and Management Sciences,* 12(5), pp.91-104.

Anderson, L. W., & Krathwohl, D. R., 2001. A Taxonomy for Learning, Teaching, and Assessing: A Revision of Bloom's Taxonomy of Educational Objectives. Allyn and Bacon. Available at https://www.theatlantic.com/ education/archive/2016/10/when-for-profit-colleges-prey-on-unsuspectingstudents/505034/. newspaper article.

Andic, S., 2006. Mobile operators must tune into youth market. *New Media Age, 7,* p.7.

André, Q., Carmon, Z., Wertenbroch, K., Crum, A., Frank, D., Goldstein, W., Huber, J., Boven, L., Weber, B. and Yang, H., 2017. Consumer Choice and Autonomy in the Age of Artificial Intelligence and Big Data. *Customer needs and solutions, 5*(2), pp.28-37.

Antonescu, G.A., Barbu, C.A. & Luchian, E.C.,2017. The analyze of E-commerce in the tourism activity. *Quality - Access to Success*, *18*, pp. 36-39.

Antons, D., & Breidbach, C. F., 2018. Big data, big insights? Advancing service innovation and design with machine learning. *Journal of Service Research, 21*(1), pp.17–39.

Appiah-Adu, K., 1999. Marketing Effectiveness and Customer Retention in the Service Sector. *The Service Industries Journal, 19*(3), pp.26-41.

Araujo, T., 2018. Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85,* pp.183–189.

Arsenyan, J., Mirowska, A. & Piepenbrink, A., 2023. Close encounters with the virtual kind: Defining a human-virtual agent coexistence framework. *Technological Forecasting and Social Change, 193, pp.234-244.*

Astrid, M., Krämer, N. C., Gratch, J., & Kang, S.-H., 2010. It doesn't matter what you are! explaining social effects of agents and avatars. *Computers in Human Behavior, 26*(6), pp.1641–1650.

Avinaash, M. & Jayam, R., 2018. Artificial Intelligence - The Marketing Game Changer. In: *International Journal of Pure and Applied Mathematics*, 119(17), pp. 1881-1890.

Baabdullah, A.M., Alalwan, A.A., Algharabat, R.S., Metri, B. & Rana, N.P., 2022. Virtual agents and flow experience: An empirical examination of AI-powered chatbots. *Technological Forecasting and Social Change*, *181*, pp. 182-188.

Balakrishnan, M., Mohomed, I. and Ramasubramanian, V., 2009. Where's that phone? Geolocating IP addresses on 3G networks. *ACM, 23*(4), pp.294–300.

Barmada, N., 2020. *Grow your business in the Nordics when Amazon Sweden launches this year*. [online] Retrieved from: <https://blog.linnworks.com/grow-your-business-across-borders-when-amazon-sweden-launches-this-year>

Bauer, H. Reichardt, T. Barnes, J. and Neumann, M., 2005. Driving consumer acceptance of mobile marketing: A theoretical framework and empirical study. *Journal of Electronic Commerce Research, 6*(3), pp.181-192

Bedi, S., 2017. Nuances of Merger and Acquisitions; DAV University, Jalandhar.

Bem, D. J., 1972. Self-perception theory. *Advances in Experimental Social Psychology, 6*, pp.1–62.

Ben Mimoun, M.S. & Poncin, I., 2015. A valued agent: How ECAs affect website customers' satisfaction and behaviors. *Journal of Retailing and Consumer Services*, *26*, pp.70-82.

Ben Mimoun, M.S., Poncin, I. & Garnier, M., 2012. Case Study-Embodied virtual agents: An analysis on reasons for failure. *Journal of Retailing and Consumer Services, 19*(6), pp. 605-612.

Ben Saad, S. & Choura, F., 2022. Effectiveness of virtual reality technologies in digital entrepreneurship: a comparative study of two types of virtual agents. *Journal of Research in Marketing and Entrepreneurship, 24*(1), pp.195-220.

Ben Saad, S. & Choura, F., 2023. Towards better interaction between salespeople and consumers: the role of virtual recommendation agent. *European Journal of Marketing, 57*(3), pp.858-903.

Ben Saad, S. & Choura, F., 2023. Towards better interaction between salespeople and consumers: the role of virtual recommendation agent. *European Journal of Marketing,* 57(3), pp.858-903.

Benbasat, I., & Wang, W., 2005. Trust in and adoption of online recommendation agents. *Journal of the association for information systems*, *6*(3), p.4.

Benlian, A., Klumpe, J., & Hinz, O., 2019. Mitigating the intrusive effects of smart home assistants by using anthropomorphic design features: A multimethod investigation. *Information Systems Journal, 27*(3), pp.212-219.

Berry, L.L., Wall, E.A. & Carbone, L.P., 2006. Service clues and customer assessment of the service experience: lessons from marketing. *Academy of Management Perspectives*, 20(2), pp. 43-57.

Bertacchini, F., Bilotta, E., & Pantano, P., 2017. Shopping with a robotic companion. *Computers in Human Behavior, 77*, pp.382–395.

Bettman, J., 1973. Perceived risk and its components: A model and empirical test. *Journal of Marketing, 10*(2), pp.184–190.

Bhattacharya, C. B., & Bolton, R. N., 2000. Relationship marketing in mass markets. *Handbook of relationship marketing, 23*(3), pp.327–354.

Bickmore, T. W., & Picard, R. W., 2005. Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction (TOCHI), 12*(2), pp.293–327.

Blake Morgan, 2021, 50 Stats Showing The Power Of Personalization https://www.forbes.com/sites/blakemorgan/2020/02/18/50-stats-showing-the-power-of-personalization/?sh=5ce6f7172a94

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R., 1956). Taxonomy of educational objectives: The classification of educational goals. *Handbook I: Cognitive Domain.*

Bodrunova, S.S. ed., 2018. *Internet Science: 5th International Conference, INSCI 2018, St. Petersburg, Russia, October 24–26, 2018, Proceedings* (Vol. 11193). Springer.

Bolton, R. N., 1998. A Dynamic Model of the Duration of the Customer's Relationship with a Continuous Service Provider: The Role of Satisfaction. *Marketing Science 17*(1), pp.45-65.

Bonacin, R., Fugini, M., Martoglia, R., & Nabuco, O. (2018, June). Web2Touch 2018: Semantic Technologies in Smart Information Sharing and Web Collaboration. In *2018 IEEE 27th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)* (pp. 251-253). IEEE.

Botsman, R., 2017. *Who can you trust?: How technology brought us together and why it might drive us apart*. PublicAffairs.

Bowen, J., Morosan, C., 2018. Beware hospitality industry: the robots are coming. *Worldwide Hospitality and Tourism Themes, 10* (6), pp.726–733.

Bowman, D., Heilman, C. M., & Seetharaman, P., 2004. Determinants of product-use compliance behavior. *Journal of Marketing Research, 41*(3), pp.324–338.

Brachten, F., Kissmer, T. and Stieglitz, S., 2021. The acceptance of chatbots in an enterprise context–A survey study. *International Journal of Information Management, 60,* p.102375.

Brandtzaeg, P.B. and Følstad, A., 2017. Why people use chatbots. In *Internet Science: 4th International Conference, INSCI 2017, Thessaloniki, Greece, November 22-24, 2017, Proceedings 4* (pp. 377-392). Springer International Publishing.

Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A., 2011. Customer engagement: Conceptual domain, fundamental propositions, and implications for research. *Journal of Service Research, 14*(3), pp.252–271. https://doi.org/10.1177/1094670511411703

Brynjolfsson, E., Rock, D. and Syverson, C., 2019. Artificial intelligence and the modern productivity paradox. *The economics of artificial intelligence: An agenda, 23*, pp.23-57.

Bucht, E. and Gillberg, R., 2015. Mobile marketing and its effects on the online impulsive purchasing tendency.

Burger, J. M., 1986. Increasing compliance by improving the deal: The that's-not-all technique. *Journal of Personality and Social Psychology, 51*(2), pp.277-283.

Burger, J. M., 1999. The foot-in-the-door compliance procedure: A multiple-process analysis and review. *Personality and Social Psychology Review, 3*(4), pp.303–325.

Burger, J. M., Soroka, S., Gonzago, K., Murphy, E., & Somervell, E., 2001. The effect of fleeting attraction on compliance to requests. *Personality and Social Psychology Bulletin, 27*(12), pp.1578–1586.

Byrnes, J. P., Miller, D. C., & Schafer, W. D., 1999. Gender differences in risk taking: A meta-analysis. *Psychological Bulletin, 125*(3), pp.367-383.

Caldarini, G., Jaf, S., & McGarry, K., 2022. A literature survey of recent advances in chatbots. *Information (Basel), 13*(1), p.41. https://doi.org/10.3390/info13010041

Callebert, L., Lourdeaux, D. and Barthès, J.P., 2016, May. Trust-based decision-making system for action selection by autonomous agents. In *2016 IEEE 20th International Conference on Computer Supported Cooperative Work in Design (CSCWD)* (pp. 4-9). IEEE.

Carter, D., 2018. How real is the impact of artificial intelligence? The business information survey 2018. *Business Information Review, 35*(3), pp.99-115.

Cassell, J., & Bickmore, T., 2003. Negotiated collusion: Modeling social language and its relationship effects in intelligent agents. *User Modeling and User-Adapted Interaction, 13*(1–2), pp.89–132.

Casteleiro-Roca, J.L., Gómez-González, J.F., Calvo-Rolle, J.L., Jove, E., Quintián, H., Martín, J.F.A., Perez, S.G., Diaz, B.G., Calero-Garcia, F. and Méndez-Perez, J.A., 2018. Prediction of the energy demand of a hotel using an artificial intelligence-based model. In *Hybrid Artificial Intelligent Systems: 13th International Conference, HAIS 2018,* *Oviedo, Spain, June 20-22, 2018, Proceedings 13* (pp. 586-596). Springer International Publishing.

Castellano, S., Khelladi, I., Charlemagne, J. & Susini, J., 2018, Uncovering the role of virtual agents in co-creation contexts: An application to the online wine business. *Management Decision, 56(*6), pp.1232-1246.

Castelo, N. and Ward, A., 2016. Political affiliation moderates attitudes towards artificial intelligence. *ACR North American Advances*.

Castelo, N., 2019. *Blurring the line between human and machine: marketing artificial intelligence*. Columbia University.

Castelo, N., Bos, M. and Lehman, D., 2018. Consumer adoption of algorithms that blur the line between human and machine. *Graduate School of Business: Columbia University Working Paper*, pp.23-37.

Chaiken, S., 1980. Heuristic versus systematic information processing and the use of source versus message cues in persuasion. *Journal of Personality and Social Psychology, 39*(5), 752-766.

Charfi, A.A. & Lombardot, E., 2015. Impact of e-atmospheric elements on the perceived value of the online visit. *Journal of Applied Business Research*, 31(1), pp.265-274.

Charlton, G., 2013. Consumers prefer live chat for customer service: stats. Retrieved from https://econsultancy.com/consumers-prefer-live-chat-for-customer-service-stats/

Chattaraman, V., Kwon, W.-., Gilbert, J.E. & Li, Y., 2014. Virtual shopping agents Persona effects for older users, *Journal of Research in Interactive Marketing, 8*(2), pp.144-162.

Chattaraman, V., Kwon, W.-., Gilbert, J.E. & Shim, S.I., 2011, Virtual agents in e-commerce: Representational characteristics for seniors, *Journal of Research in Interactive Marketing, 5*(4), pp.276-297.

Chatterjee, S., Ghosh, S.K., Chaudhuri, R. and Nguyen, B., 2019, Are CRM systems ready for AI integration? A conceptual framework of organizational readiness for effective AI-CRM integration. *The Bottom Line, 32*(2), pp.144-157. https://doi.org/10.1108/BL-02-2019-0069

Chen, Y., Lee, J.-Y., Sridhar, S. (hari), Mittal, V., McCallister, K., & Singal, A. G., 2020. Improving cancer outreach effectiveness through targeting and economic assessments: Insights from a randomized field experiment. *Journal of Marketing, 84*(3), pp.1–27. https://doi.org/10.1177/0022242920913025

Cialdini, R. B., & Goldstein, N. J., 2004. Social influence: Compliance and conformity. *Annual Review of Psychology, 55*, pp.591–621.

Cialdini, R. B., 2001. Harnessing the science of persuasion. *Harvard Business Review, 79*(9), pp.72–81.

Cialdini, R. B., Vincent, J. E., Lewis, S. K., Catalan, J., Wheeler, D., & Darby, B. L., 1975. Reciprocal concessions procedure for inducing compliance: The door-in-the-face technique. *Journal of Personality and Social Psychology, 31*(2), pp.206-215.

Cialdini, R. B., Wosinska, W., Barrett, D. W., Butner, J., & Gornik-Durose, M., 1999. Compliance with a request in two cultures: The differential influence of social proof and commitment/consistency on collectivists and individualists. *Personality and Social Psychology Bulletin, 25*(10), pp.1242–1253.

Cialdini, R.B. and Garde, N., 1987. Influence (vol. 3). *Port Harcourt: A. Michel*.

Cialdini, R.B. and Trost, M.R., 1998. Social influence: Social norms, conformity and compliance.

Cialdini, R.B., 2009. *Influence: Science and practice* (Vol. 4, pp. 51-96). Boston: Pearson education.

Clark, S., 2020. 4 Ways That AI Is Improving the Customer Experience. Available at: https://www.cmswire.com/customer-experience/4-ways-that-ai-is-improving-the-customer-experience/

Collins, C., Dennehy, D., Conboy, K., & Mikalef, P., 2021. Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management, 60*(10), p.102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

Contreras, C.R. and Valette-Florence, P., 2022, May. Toward a Theoretical Model of Branded Chatbot Adoption, a Bibliometric and Machine Learning Perspective: An Abstract. In *Academy of Marketing Science Annual Conference* (pp. 181-182). Cham: Springer Nature Switzerland.

Coopers, P., 2018. Künstliche Intelligenz als Innovationsbeschleuniger in Unternehmen – Zuversicht und Vertrauen in Künstliche Intelligenz. [online] Available at: https://www.pwc.de/de/digitale-transformation/ki-als-innovationsbeschleuniger-in-unternehmen-whitepaper.pdf

Corritore, C.L., Kracher, B. and Wiedenbeck, S., 2003. On-line trust: concepts, evolving themes, a model. *International journal of human-computer studies*, *58*(6), pp.737-758.

Cuciniello, M., Amorese, T., Greco, C., Raimo, G., Cordasco, G., Kornes, M.S., Johansen, A.T., Gjellesvik, K.B., Fernandez, A., Kyslitska, D. and González-Fraile, E., 2022, September. A cross-cultural survey to identify Seniors' preferences towards the Empathic Virtual Coach. In *2022 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)* (pp. 1-6). IEEE.

Dalen, D.M., Moen, E.R. and Riis, C., 2006. Contract renewal and incentives in public procurement. *International Journal of Industrial Organization*, *24*(2), pp.269-285.

Daqar, M. A. M. A., &Smoudy, A. K. A., 2019. The role of artificial intelligence on enhancing customer experience. *International Review of Management and Marketing*, *9*(4), pp.22–31.

Daqar, Mohannad A.M. Abu; Smoudy, Ahmad K. A., 2019. The Role of Artificial Intelligence on Enhancing Customer Experience. *International Review of Management and Marketing, 9*(4), pp.22–31.

Davenport, T., Guha, A., Grewal, D. & Bessgott, T., 2020. How artificial intelligence intelligence will change the future of marketing. *Journal of the Academy of Marketing Science, 48,* pp.24-42

Davenport, T., Guha, A., Grewal, D., & Bressgott, T., 2020. How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), pp.24–42. https://doi.org/10.1007/s11747-019-00696-0

Davis, B. P., & Knowles, E. S., 1999. A disrupt-then-reframe technique of social influence. *Journal of Personality and Social Psychology, 76*(2), pp.192-199.

Dawar, N. and Bendle, N., 2018. Marketing in the age of Alexa. *Harvard Business Review*, *96*(3), pp.80-86.

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.

Derrick, D. C., Jenkins, J. L., & Nunamaker Jr., J. F., 2011. Design principles for special purpose, embodied, conversational intelligence with environmental sensors (SPECIES) agents. *AIS Transactions on Human-Computer Interaction, 3*(2), pp.62–81.

Deutsch, M., & Gerard, H. B., 1955. A study of normative and informational social influences upon individual judgment. *The Journal of Abnormal and Social Psychology, 51*(3), pp.629-636.

Devare, M., 2018. Preparation of raspberry pi for iot-enabled applications. In *Protocols and Applications for the Industrial Internet of Things* (pp. 264-308). IGI Global.

Deventer, C. and Zidda, P., 2023, May. Adoption of Virtual Agents in Healthcare E-Commerce: A Perceived Value Perspective. In *International Conference on Research Challenges in Information Science* (pp. 256-271). Cham: Springer Nature Switzerland.

Dickinger, A. and Murphy, J., 2005. Diffusion and success factors of mobile marketing. *Electronic commerce research and applications*, *4*(2), pp.159-173.

Ding, A. W., & Li, S., 2019. Herding in the consumption and purchase of digital goods and moderators of the herding bias. *Journal of the Academy of Marketing Science*, *47*(3), pp.460–478. https://doi.org/10.1007/s11747-018-0619-0

Dostál, M. and Skrbek, J., 2021. Automation of Service Desk: Knowledge Management Perspective. In *KMIS* (pp. 204-210).

Du Plessis, P.J., 1990. *Consumer behaviour: a South African perspective*. Southern Book Publishers.

Duan, W., Gu, B. and Whinston, A.B., 2009. Informational cascades vs. network externalities: An empirical investigation of herding on software downloading. *MIS Quarterly, 33*(1), pp.23-48.

Dugdale, J., Pallamin, N. and Pavard, B., 2006. An assessment of a mixed reality environment: Toward an ethnomethodological approach. *Simulation & Gaming, 37*(2), pp.226-244.

Dzyabura, D. and Hauser, J.R., 2019. Recommending products when consumers learn their preference weights. *Marketing Science, 38*(3), pp.417-441.

E Norberg, H., Nettelbladt, K. and Nilsson, P., 2023. Social agents, stereotypes and adoption: Exploring the effects of stereotypes on social agent interaction and examining patterns of social agent adoption.

Edwards, A., Edwards, C., Spence, P.R., Harris, C. and Gambino, A., 2016. Robots in the classroom: Differences in students' perceptions of credibility and learning between "teacher as robot" and "robot as teacher". *Computers in Human Behavior, 65*, pp.627-634.

Elish, M.C. and Boyd, D., 2018. Situating methods in the magic of Big Data and AI. *Communication monographs, 85*(1), pp.57-80.

Elkins, A.C., Derrick, D.C., Burgoon, J.K. & Nunamaker Jr, J.F., 2012. Predicting users' perceived trust in Embodied Conversational Agents using vocal dynamics. In:

*Proceedings of the 45th Hawaii International Conference on System Science*. Maui: IEEE.

Engel, J., Blackwell, R.D. & Miniard, P., 1995. *Consumer Behavior*. 8th ed. Fort Worth, TX: Dryden.

Epley, N., Waytz, A. & Cacioppo, J.T., 2007. On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, 114(4), pp. 864–866.

Ericksen, M.K. & Sirgy, M.J., 1989. Achievement motivation and clothing behaviour: A self-image congruence analysis. *Journal of Social Behavior and Personality*, 4(4), pp. 307–326.

Erickson, T., 2012. How mobile technologies are shaping a new generation. *Harvard Business Review*, 90(5), pp. 1-5.

Esmahi, L., 2008. Contract negotiation in e-marketplaces: A model based on dependency relations. *Journal of Electronic Commerce in Organizations*, 6(3), pp. 74-91.

Esposito, A., Amorese, T., Cuciniello, M., Riviello, M.T., Esposito, A.M., Troncone, A. & Cordasco, G., 2021. Elder user’s attitude toward assistive virtual agents: the role of voice and gender. *Journal of Ambient Intelligence and Humanized Computing*, 12, pp. 4429-4436.

Etemad-Sajadi, R., 2014. The influence of a virtual agent on web-users' desire to visit the company: The case of restaurant's website. *International Journal of Quality & Reliability Management*, 31(4), pp. 419-434.

Etemad-Sajadi, R., 2016. The impact of online real-time interactivity on patronage intention: The use of avatars. *Computers in Human Behavior*, 61, pp. 227–232.

European Commission, 2018. A definition of AI: Main Capabilities and Disciplines. [Online] Available at: https://ec.europa.eu/digital-single-market/en/news/definition-artificial-intelligence-main-capabilities-and-scientific-disciplines.

Eyssel, F., Hegel, F., Horstmann, G. & Wagner, C., 2010. Anthropomorphic inferences from emotional nonverbal cues: A case study. In: *Proceedings of the 19th International Symposium in Robot and Human Interactive Communication*. Viareggio: IEEE.

Facebook, 2019. F8 2019: Making It Easier for Businesses to Connect with Customers on Messenger. Available at: https://www.facebook.com/business/news/f8-2019-making-it-easier-for-businesses-to-connect-with-customers-on-messenger [Accessed date].

Feine, J., Gnewuch, U., Morana, S. & Maedche, A., 2019. A taxonomy of social cues for conversational agents. *International Journal of Human-Computer Studies*, 132, pp. 138–161.

Fernandes, T. & Oliveira, E., 2021. Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, 122, pp. 180-191.

Ferrucci, D., Brown, E., Chu-Carroll, J., Fan, J., Gondek, D., Kalyanpur, A. et al., 2010. Building Watson: An overview of the DeepQA project. *AI Magazine*, 31(3), pp. 59–79.

Fogg, B.J. & Nass, C., 1997. Silicon sycophants: The effects of computers that flatter. *International Journal of Human-Computer Studies*, 46(5), pp. 551–561.

Følstad, A., Nordheim, C.B. & Bjørkli, C.A., 2018. What makes users trust a chatbot for customer service? An exploratory interview study. In: Internet Science. Springer International Publishing, pp. 194–208.

Fornell, C. & Larcker, D.F., 1981. Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 18(3), pp. 382–388.

Freedman, J.L. & Fraser, S.C., 1966. Compliance without pressure: The foot-in-the-door technique. *Journal of Personality and Social Psychology*, 4(2), pp. 195–202.

Fryer, L.K. & Carpenter, R., 2006. Bots as language learning tools. *Language Learning & Technology*, 10(3). DOI: 10.1.1.25/44068

Gacanin, H. & Wagner, M., 2019. Artificial intelligence paradigm for customer experience management in next-generation networks: Challenges and perspectives. *IEEE Network*, 33(2), pp. 188–194. https://doi.org/10.1109/mnet.2019.1800015

Gana, M. & Koce, H., 2016. Mobile Marketing: The Influence of Trust and Privacy Concerns on Consumers' Purchase Intention. *International Journal of Marketing Studies*, 8(2), pp. 121-127.

Gans, J., Agrawal, A. & Goldfarb, A., 2017. How AI will change strategy: A thought experiment. *Harvard Business Review Online*. Retrieved from https://hbr.org/product/how-ai-will-change-strategy-a-thought-experiment/H03XDI-PDF-ENG on November 29, 2021.

Gao, L., 2020. Technology advancements for whistleblowing reporting platforms and employees' decision to blow the whistle. *Accounting and the Public Interest*, 20(1), pp. 172-192.

Gefen, D. & Straub, D., 2003. Managing user trust in B2C e-services. *e-Service*, 2(2), pp. 7-24.

Gerard du Toit, Anderson, J. & Hatherall, R., 2020. Customer Experience Tools and Trends: Let No Tool Stand Alone. Bain & Company. Retrieved from https://www.bain.com/insights/customer-experience-tools-and-trends-2020-let-no-tool-stand-alone/

Gnewuch, U., Morana, S. & Maedche, A., 2017. Towards designing cooperative and social conversational agents for customer service. In: Proceedings of the 38th International Conference on Information Systems (ICIS). Seoul: AISel.

Go, E. & Sundar, S.S., 2019. Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, 97, pp. 304–316.

Gönül, F.F. & Ter Hofstede, F., 2006. How to compute optimal catalog mailing decisions. *Marketing Science*, 25(1), pp. 65–74.

Görgens, M., 2019. How can Artificial Intelligence use big data to form a better customer experience.

Gray, K., 2017. AI can be a troublesome teammate. *Harvard Business Review*, July 20. Retrieved from https://hbr.org/2017/07/ai-can-be-a-troublesome-teammate on November 29, 2021.

Grönroos, C., 1995. Relationship Marketing: The Strategy Continuum. *Journal of the Academy of Marketing Science*, 23(4), pp. 252-254.

Grönroos, C., 1997. From marketing mix to relationship marketing: Towards a paradigm shift in marketing. *Management Decision*, 35(4), pp. 322-339.

Guo, J., Zhang, W., Fan, W. & 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. https://doi.org/10.1080/07421222.2018.1523564

Gupta, S. & Mathur, N., 2023. Virtual communication adoption by educational leaders: moderating role of perceived risk and benefits. *The International Journal of Information and Learning Technology*, 40(3), pp. 242-258.

Gustafsod, P.E., 1998. Gender Differences in risk perception: Theoretical and methodological perspectives. *Risk Analysis*, 18(6), pp. 805–811.

Gustafsson, A., Johnson, M.D. & Roos, I., 2005. The effects of customer satisfaction, relationship commitment dimensions, and triggers on customer retention. *Journal of Marketing*, 69(4), pp. 210–218.

Ha, Q.A., Chen, J.V., Uy, H.U. & Capistrano, E.P., 2020. Exploring the privacy concerns in using intelligent virtual assistants under perspectives of information sensitivity and anthropomorphism. *International Journal of Human–Computer Interaction*, 36(17), pp. 1-16.

Hair, J.F., Risher, J.J., Sarstedt, M. & Ringle, C.M., 2019. When to use and how to report the results of PLS-SEM. *European Business Review*.

Hall, J., 2019. How Artificial Intelligence Is Transforming Digital Marketing. Forbes. Available at: https://www.forbes.com/sites/forbesagencycouncil/2019/08/21/how-artificial-intelligence-is-transforming-digital-marketing/?sh=7d9c632321e1 [Accessed 29 November 2021].

Hall, J., 2019. How Artificial Intelligence Is Transforming Digital Marketing. *Forbes*. Available at: https://www.forbes.com/sites/forbesagencycouncil/2019/08/21/how-artificial-intelligence-is-transforming-digital-marketing/?sh=34ae66a821e1.

Hancock, P.A., Billings, D.R., Schaefer, K.E., Chen, J.Y., de Visser, E.J. & Parasuraman, R., 2011. A meta-analysis of factors affecting trust in human-robot interaction. *Human Factors*, 53(5), pp. 517-527. https://doi.org/10.1177/0018720811417254

Hasan, S., Godhuli, E.R., Rahman, M.S. & Al Mamun, M.A., 2023. The adoption of conversational assistants in the banking industry: is the perceived risk a moderator? *Heliyon*, 9(9).

Hayes, A.F., 2017. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 2nd ed. New York: Guilford Publications.

Herzenstein, M., Dholakia, U.M. & Andrews, R.L., 2011. Strategic herding behavior in peer-to-peer loan auctions. *Journal of Interactive Marketing*, 25(1), pp. 27-36.

Hess, T.J., Fuller, M. & Campbell, D.E., 2009. Designing interfaces with social presence: Using vividness and extraversion to create social recommendation agents. *Journal of the Association for Information Systems*, 10(12), pp. 889-991.

Hill, J., Ford, W.R. & 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, S.M., Ocasio-Velázquez, M. & Booth, C., 2017. Trust or consequences? Causal effects of perceived risk and subjective norms on cloud technology adoption. *Computers & Security*, 70, pp. 581-595.

Hollebeek, L., 2011b. Exploring customer brand engagement: definition and themes. *Journal of Strategic Marketing*, 19(7), pp. 555–573.

Hollebeek, L.D., 2011a. Demystifying customer brand engagement: exploring the loyalty nexus. *Journal of Marketing Management*, 27(7-8), pp. 785–807. https://doi.org/10.1080/0267257X.2010.500132

Holtgraves, T., Ross, S.J., Weywadt, C. & Han, T., 2007. Perceiving artificial social agents. *Computers in Human Behavior*, 23(5), pp. 2163–2174.

Holzwarth, M., Janiszewski, C. & Neumann, M.M., 2006. The influence of avatars on online consumer shopping behavior. *Journal of Marketing*, 70(4), pp. 19–36.

Hopkins, B. & Silverman, A., 2016. The Top Emerging Technologies To Watch: 2017 To 2021. Forrester. Available at: https://www.forrester.com/report/The+Top+Emerging+Technologies+To+Watch+2017+To+2021/-/E-RES133144 [Accessed date].

Hoy, M.B., 2018. Alexa, Siri, Cortana, and more: An introduction to voice assistants. *Medical Reference Services Quarterly*, 37(1), pp. 81–88.

Huang, A., Chao, Y., de la Mora Velasco, E., Bilgihan, A. & Wei, W., 2022. When artificial intelligence meets the hospitality and tourism industry: an assessment framework to inform theory and management. *Journal of Hospitality and Tourism Insights*, 5(5), pp. 1080-1100

IBM Watson Marketing, n.d. How AI is changing marketing. *Business Insider*. Available at: https://www.businessinsider.com/sc/how-ai-is-changing-marketing?IR=T [Accessed date].

Itani, O.S. & Hollebeek, L.D., 2021. Light at the end of the tunnel: Visitors' virtual reality (versus in-person) attraction site tour-related behavioral intentions during and post-COVID-19. *Tourism Management*, 84, p.104290

JafarSadhik, 2021. 5 ways AI is changing customer experience. *Geospatial World*. Available at: https://www.geospatialworld.net/blogs/guest-blogs/5-ways-ai-is-changing-customer-experience/

Jarrahi, M.H., 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), pp. 577-586.

Jin, S.-A.A. & Sung, Y., 2010. The roles of spokes-avatars' personalities in brand communication in 3D virtual environments. *Journal of Brand Management*, 17(5), pp. 317–327.

Jin, S.A.A., 2009. The roles of modality richness and involvement in shopping behavior in 3D virtual stores. *Journal of Interactive Marketing*, 23(3), pp. 234–246.

Joshi, S., Chirputkar, A. & Jog, Y., 2015. Influence of brand oriented factors on customer loyalty of prepaid mobile services. *Indian Journal of Science and Technology*, 8(S6), p.43. https://doi.org/10.17485/ijst/2015/v8is6/62119

Jung, D., Dorner, V., Glaser, F. & Morana, S., 2018a. Robo-advisory. *Business & Information Systems Engineering*, 60(1), pp. 81–86.

Jung, D., Dorner, V., Weinhardt, C. & Pusmaz, H., 2018b. Designing a robo-advisor for risk-averse, low-budget consumers. *Electronic Markets*, 28(3), pp. 367–380.

Justo, A.V., Reis, J.C.D., Calado, I., Bonacin, R. & Jensen, F.R., 2018. Exploring ontologies to improve the empathy of interactive bots. In: *2018 IEEE 27th International*

*Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE)*, p. 267.

Kaka, N., Madgavkar, A., Kshirsagar, A., Gupta, R., Manyika, J., Bahl, K. & Gupta, S., 2019. Digital India: Technology to transform a connected nation. *McKinsey & Company*. Available at: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/digital-india-technology-to-transform-a-connected-nation

Karakaya, F. & Ganim Barnes, N., 2010. Impact of online reviews of customer care experience on brand or company selection. *The Journal of Consumer Marketing*, 27(5), pp. 447–457. https://doi.org/10.1108/07363761011063349

Kauffman, J.R. & Li, X., 2003. Payoff externalities, informational cascades and managerial incentives: a theoretical framework for IT adoption herding. *INFORMS Conference on IS and Technology*, Atlanta.

Kazoun, N., Kokkinaki, A. & Chedrawi, C., 2022. Factors that Affects the Use of AI Agents in Adaptive Learning: A Sociomaterial and Mcdonaldization Approach in the Higher Education Sector.

Ketter, W., Peters, M., Collins, J. & Gupta, A., 2016. A multiagent competitive gaming platform to address societal challenges. *MIS Quarterly: Management Information Systems*, 40(2), pp. 447-460.

Khanna, N. & Mathews, R.D., 2011. Can herding improve investment decisions? *RAND Journal of Economics*, 42(1), pp. 150–174.

Kim, D., Ferrin, D.L. & Rao, H.R., 2008. A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, 44(2), pp. 544-564.

Kim, Goh, J. & Jun, S., 2018. The use of voice input to induce human communication with banking chatbots. In: *Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction*.

Kim, H.-S. & Yoon, C.-H., 2004. Determinants of subscriber churn and customer loyalty in the Korean mobile telephony market. *Telecommunications Policy*, 28(9-10), pp. 751-765.

Kirikova, M., 2015. Work systems paradigm and frames for fractal architecture of information systems.

Klabi, H. & Mellouli, K., 2006. A negotiation model for the supply chain based on creative multi-agent proposition of a negotiation model for an invitation for tenders treatment. In: *Proceedings - ICSSSM'06: 2006 International Conference on Service Systems and Service Management*, pp. 841.

Klumpe, J., Koch, O.F. & Benlian, A., 2019. How pull vs. push information delivery and social proof affect information disclosure in location based services. *Electronic Markets*. https://doi.org/10.1007/s12525-018-0318-1

Knowles, E.S. & Linn, J.A., 2004. Approach-avoidance model of persuasion: Alpha and omega strategies for change. In *Resistance and Persuasion* (pp. 117–148). Mahwah: Lawrence Erlbaum Associates Publishers.

Kocakoç, İ.D., 2022. The Role of Artificial Intelligence in Health Care.

Kotler, P. & Armstrong, G., 2010. *Principles of Marketing*, 13th ed. Pearson Education.

Kotler, P. & Keller, K., 2009. *Marketing Management*, 14th ed. Upper Saddle River, N.J.: Pearson Prentice Hall.

Kressmann, F., Sirgy, M.J., Herrmann, A., Huber, F., Huber, S. & Lee, D.J., 2006. Direct and indirect effects of self-image congruence on brand loyalty. *Journal of Business Research*, 59(9), pp. 955–964.

Kujur, R., Jena, S. & Soma, 2015. A Study on Perceived Service Quality of IDEA Cellular Ltd. - A Case Study on Factor Analysis. *Journal of Business and Management Sciences*, 3(1), pp. 53-57.

Kull, A.J., Romero, M. & Monahan, L., 2021. How may I help you? Driving brand engagement through the warmth of an initial chatbot message. *Journal of Business Research*, 135, pp. 840-850.

Kumar, V., Rajan, B., Venkatesan, R. & Lecinski, J., 2019. Understanding the role of artificial intelligence in personalized engagement marketing. *California Management Review*, 61(4), pp. 135–155. https://doi.org/10.1177/0008125619859317

Lacewing, M., 2010. Personal identity: Physical and psychological continuity theories.

Lacity, M., Willcocks, L. & Craig, A., 2017. Service automation: cognitive virtual agents at SEB bank. *The Outsourcing Unit Working Research Paper Series*, 17(01).

Lai, H., 2000. An object-oriented architecture for intelligent virtual receptionists. *International Journal of Electronic Commerce*, 4(3), pp. 69-86.

Langford, S. & Ramachandran, M., 2013. The products of fission, fusion, and teletransportation: An occasional identity theorist's perspective. *Australasian Journal of Philosophy*, 91(1), pp. 105–117.

Larivière, B., Bowen, D., Andreassen, T.W., Kunz, W., Sirianni, N.J., Voss, C., et al., 2017. Service encounter 2.0: An investigation into the roles of technology, employees and customers. *Journal of Business Research*, 79, pp. 238–246.

Lau, H.C.W., Wong, C.W.Y., Pun, K.F. & Chin, K.S., 2003. Virtual agent modeling of an agile supply chain infrastructure. *Management Decision*, 41(7), pp. 625-634.

Launchbury, J., 2018. A DARPA perspective on artificial intelligence. Available at: https://www.darpa.mil/attachments/AIFull.pdf

Lee, J., Park, D. & Han, I., 2008. The effect of negative online consumer reviews on product attitude: an information processing view. *Electronic Commerce Research and Applications*, 7(3), pp. 341-352.

Lee, S.K., Kavya, P. & Lasser, S.C., 2021. Social interactions and relationships with an intelligent virtual agent. *International Journal of Human-Computer Studies*, 150, 102608.

Lemoine, J.- & Notebaert, J.-, 2009. L'influence des agents virtuels sur la confiance des internautes vis-à-vis d'un site Web. In: *Innovation and Knowledge Management in Twin Track Economies: Challenges and Solutions - Proceedings of the 11th International Business Information Management Association Conference, IBIMA 2009*, pp. 1660.

Lemoine, P.J.- & Cherif, E., 2014. The contribution of the technologies adoption theories and perceptual models in understanding users' responses to virtual advisors: Proposal for an integrator model. In: *Proceedings of the 24th International Business Information Management Association Conference - Crafting Global Competitive Economies: 2020 Vision Strategic Planning and Smart Implementation*, pp. 122.

Li, R., Wang, Q., Zhang, X., Wang, Q., Galindo, D. & Xiang, Y., 2021. An offline delegatable cryptocurrency system. *IEEE International Conference on Blockchain and Cryptocurrency, ICBC 2021*.

Li, Y. & Shin, H., 2022. Should a Luxury Brand's Chatbot Use Emoticons? An Abstract.

Liao, C., Palvia, P. & Chen, J.L., 2009. Information technology adoption behavior life cycle: Toward a technology continuance theory (TCT). *International Journal of Information Management,* 29(4), pp. 309–320.

Ling, E.C., Tussyadiah, I., Tuomi, A., Stienmetz, J. & Ioannou, A., 2021. Factors influencing users' adoption and use of conversational agents: A systematic review. *Psychology & Marketing*, 38(7), pp. 1031-1051.

Lisetti, C., Amini, R., Yasavur, U. & Rishe, N., 2013. I can help you change! An empathic virtual agent delivers behavior change health interventions. *ACM Transactions on Management Information Systems (TMIS)*, 4(4).

Llanas, R., 2019. The future of mobile marketing is in artificial intelligence. Available at: https://www.mobilemarketingmagazine.com/the-future-of-mobile-marketing-is-in-artificial-intelligence

Loudon, D.L. & Bitta, A.J.D., 1993. *Consumer Behavior: Concepts and Applications*, 4th ed. McGraw-Hill.

Luger, E. & Sellen, A., 2016. Like having a really bad PA: The gulf between user expectation and experience of conversational agents. In: *Proceedings of the CHI Conference on Human Factors in Computing Systems*.

Lunardo, R., Bressolles, G. & Durrieu, F., 2016. The interacting effect of virtual agents' gender and dressing style on attractiveness and subsequent consumer online behavior. *Journal of Retailing and Consumer Services*, 30, pp. 59-66.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T. et al., 2019. AI-based digital assistants. *Business & Information Systems Engineering*, 61(4), pp. 535-544.

Makridakis, S., 2017. The forthcoming artificial intelligence (AI) revelation: Its impact on society and firms. *Futures*, 90, pp. 46–60.

Marketing Evolution, 2020. Top 5 Trends for Influencer Marketing in 2020. Available at: https://sociopuff.com/top-5-trends-for-influencer-marketing-in-2020

Marketing Evolution, 2021. AI Marketing. Available at: https://www.marketingevolution.com/marketing-essentials/ai-markeitng

Maxwell, A.L., Jeffrey, S.A. & Lévesque, M., 2011. Business angel early stage decision making. *Journal of Business Venturing*, 26(2), pp. 212–225. https://doi.org/10.1016/j.jbusvent.2009.09.002

May, P. & Kirwan, G., 2013. Virtual Assistants: Trust and adoption in telecommunication customer support. In: *Cyberpsychology and New Media* (pp. 75-90). Psychology Press.

Mayer, R.C., Davis, J.H. & Schoorman, F.D., 1995. An integrative model of organizational trust. *Academy of Management Review*, 20(3), pp. 709-734. https://doi.org/10.5465/amr.1995.9508080335

Mcguire, W.J., 1974. Psychological motives and communication gratification. In: J.G. Blumler & E. Katz (Eds.), *The Uses of Mass Communications*. Sage Publications.

McNeill, F. & Bundy, A., 2010. Facilitating interaction between virtual agents by changing ontological representation. In: *Encyclopedia of E-Business Development and Management in the Global Economy*, pp. 934-941.

Mehta, B.S., 2013. Capabilities costs networks and innovations: impact of mobile phones in rural India. Institute for Human Development, New Delhi.

Mero, J., 2018. The effects of two-way communication and chat service usage on consumer attitudes in the e-commerce retailing sector. *Electronic Markets*, 28(2), pp. 205–217.

Meuter, M.L., Bitner, M.J., Ostrom, A.L. & Brown, S.W., 2005. Choosing among alternative service delivery modes: An investigation of customer trial of self-service technologies. *Journal of Marketing*, 69(2), pp. 61–83.

Mimoun, M.S.B., Poncin, I. & Garnier, M., 2017. Virtual Sales Agents: The Reasons of Failure.

Mirbagheri, S. & Hejazinia, M., 2010. Mobile marketing communication: Learning.

Mobile Advertising, 2018. AI Transforming Mobile Marketing. Available at: https://www.businessofapps.com/insights/ai-transforming-mobile-marketing/ [Accessed date].

Mobile Artificial Intelligence Market - Growth, Trends, Covid-19 Impact, And Forecasts (2022 - 2027). Available at: https://www.mordorintelligence.com/industry-reports/mobile-artificial-intelligence-market [Accessed date].

Mohammed, B., Stefan, D., Alexander, D., Sushil, M., Federico, M., Maarten, P., Prateek, R., Michael, S. & Yann, S., 2018. Global Payments 2018: Reimagining the customer experience. The Boston Consulting Group (BCG). Available at: https://www.bcg.com/enin/publications/2018/global-payments-reimagining-customer-experience [Accessed date].

Montgomery, D.C. & Runger, G.C., 2003. *Applied Statistics and Probability for Engineers*. John Wiley & Sons.

Moon, B.J., 2004. Consumer adoption of the internet as an information search and product purchase channel: some research hypotheses. *International Journal of Internet Marketing and Advertising*, 1(1), pp. 104-118.

Moon, Y. & Nass, C., 1996. How real are computer personalities? Psychological responses to personality types in human-computer interaction. *Communication Research*, 23(6), pp. 651–674.

Mori, M., 1970. The uncanny valley. *Energy*, 7(4), pp. 33–35.

Morris, C., Schlenoff, C. & Srinivasan, V., 2017. A remarkable resurgence of artificial intelligence and its impact on automation and autonomy. *IEEE Transactions on Automation Science and Engineering*, 14(2), pp. 407-409.

Muhammad, A., Masa'deh, B. & Alkurdi, 2012. The Effect of Customer Satisfaction upon customer Retention in the Jordanian Mobile Market: An Empirical Investigation. *European Journal of Economics, Finance and Administrative Sciences*, Issue 47.

Murphy, E.C. & Murphy, M.A., 2002. *Leading on the edge of chaos: The 10 critical elements for success in volatile times*. Prentice Hall Press.

Murray, G. & Wardley, M., 2014. The math of modern marketing: How predictive analytics makes marketing more effective. IDC White Paper. Available at: http://www.sap.com/bin/sapcom/en_us/downloadasset.2014-06-jun-12-15.the-math-of-modern-marketing-howpredictive-analyticsmakes-marketing-more-effective-pdf.bypassReg.html

Nagy, S., Hajdu, N., 2021. Consumer acceptance of the use of artificial intelligence in online shopping: Evidence from Hungary. *Amfiteatru Economic*, 23(56), p. 155. https://doi.org/10.24818/ea/2021/56/155

Nanji, A., 2019. How consumers feel about brands' use of AI. *MarketingProfs*. Available at: https://www.marketingprofs.com/charts/2019/41489/how-consumers-feel-about-brands-use-of-ai [Accessed date].

Nanji. A, 2019. How consumers feel about brands' use of AI. Retrieved from https://www.marketingprofs.com/

Nashold Jr, D.B., 2020. Trust in Consumer Adoption of Artificial Intelligence-Driven Virtual Finance Assistants: A Technology Acceptance Model Perspective. Doctoral dissertation, The University of North Carolina at Charlotte.

Nasır, S., 2017. Customer retention strategies and customer loyalty. In *Advertising and Branding*. IGI Global, pp. 1178–1201.

Nass, C. & Moon, Y., 2000. Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), pp. 81–103.

Nass, C., Moon, Y. & Carney, P., 1999. Are people polite to computers? Responses to computer-based interviewing systems. *Journal of Applied Social Psychology*, 29(5), pp. 1093–1109.

Nass, C., Moon, Y. & Green, N., 1997. Are machines gender neutral? Gender-stereotypic responses to computers with voices. *Journal of Applied Social Psychology*, 27(10), pp. 864–876.

Nass, C., Steuer, J. & Tauber, E.R., 1994. Computers are social actors. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.

Natter, M., Reutterer, T., Mild, A. & Taudes, A., 2007. Practice prize report: An assortment-wide decision-support systems for dynamic pricing and promotion planning in DIY retailing. *Marketing Science*, 26(4), pp. 576–583.

Netzer, O., Lemaire, A. & Herzenstein, M., 2019. When words sweat: Identifying signals for loan default in the text of loan applications. *Journal of Marketing Research*, 56(6), pp. 960–980. https://doi.org/10.1177/0022243719852959

Neves, P. & Eisenberger, R., 2012. Management communication and employee performance: the contribution of perceived organisational support. *Human Performance*, 25(5), pp. 452–464. https://doi.org/10.1080/08959285.2012.721834

Newell, A. & Simon, H.A., 1963. GPS, a program that simulates human thought. In *Computers and Thought.* MIT Press, Cambridge, pp. 279-293.

Newell, A. & Simon, H.A., 1976. Computer science as empirical enquiry: Symbols and search. *Communications of the ACM*, 19, pp. 113-126.

Nikhashemi, S.R., Knight, H.H., Nusair, K. & Liat, C.B., 2021. Augmented reality in smart retailing: A (n)(a) symmetric approach to continuous intention to use retail brands' mobile AR apps. *Journal of Retailing and Consumer Services*, 60, 102464.

Nunnally, J. & Bernstein, I., 1994. *Psychometric Theory*, 3rd ed. New York: McGraw Hill Inc.

Nye, B.D. & Silverman, B.G., 2013. Social learning and adoption of new behavior in a virtual agent society. *Presence*, 22(2), pp. 110-140.

Olson, J. & Mourey, J.A., 2019. Greater expectations: Anthropomorphic products must be warm and competent... or else. *ACR North American Advances*.

Onete, B., Constantinescu, M. & Filip, A., 2008. Internet buying behavior. Case study: research of AES students' behavior regarding online shopping. *Amfiteatru Economic*, November, pp.18-24.

Orlowski, A., 2017. Facebook scales back AI flagship after chatbots hit 70% f-AI-lure rate. Retrieved from https://www.theregister.co.uk/2017/02/22/facebook_ai_fail/

Ossowska, K., Szewc, L., Weichbroth, P., Garnik, I. & Sikorski, M., 2016. Exploring an ontological approach for user requirements elicitation in the design of online virtual agents.

Ovalle, D.A., Salazar, O.M. & Duque, N.D., 2014. Customized recommendation model for virtual courses based on ubiquitous computing and intelligent agents. *Informacion Tecnologica*, 25(6), pp. 131-142.

Pantano, E. & Pizzi, G., 2020. Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services*, 55, p.102096. https://doi.org/10.24818/ea/2021/56/155

Parenti, L., Marchesi, S., Belkaid, M. & Wykowska, A., November 2021. Exposure to robotic virtual agent affects adoption of intentional stance. In *Proceedings of the 9th International Conference on Human-Agent Interaction* (pp. 348-353).

Pavlikova, L., Schmid, B.F., Maass, W. & Müller, J.P., 2003. Editorial: Software agents. *Electronic Markets*, 13(1), pp. 1–2.

Petelina-Walsh, A., 2022. Exploring the Role of Human and Digital Interactions in Online Customer Support: An Abstract.

Pfeuffer, N., Adam, M., Toutaoui, J., Hinz, O. & Benlian, A., 2019a. Mr. and Mrs. Conversational Agent - Gender stereotyping in judge-advisor systems and the role of egocentric bias. *International Conference on Information Systems (ICIS)*, Munich.

Pfeuffer, N., Benlian, A., Gimpel, H. & Hinz, O., 2019b. Anthropomorphic information systems. *Business & Information Systems Engineering*, 61(4), pp. 523–533.

Pickard, M.D., Burgoon, J.K. & Derrick, D.C., 2014. Toward an objective linguistic-based measure of perceived embodied conversational agent power and likeability. *International Journal of Human-Computer Interaction*, 30(6), pp. 495–516.

Pickard, M.D., Schuetzler, R., Valacich, J.S. & Wood, D.A., 2020. Innovative accounting interviewing: A comparison of real and virtual accounting interviewers. *Accounting Review*, 95(6), pp. 339-366.

Pitt, C.S., Bal, A.S. & Plangger, K., 2020. New approaches to psychographic consumer segmentation: Exploring fine art collectors using artificial intelligence, automated text analysis and correspondence analysis. *European Journal of Marketing*. https://doi.org/10.1108/EJM-01-2019-0083

Pizlo, W. & Parzonko, A., 2021. Virtual Organizations and Trust. In *Trust, Organizations and the Digital Economy: Theory and Practice*, pp. 61-78.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. & Podsakoff, N.P., 2003. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), pp. 879–903.

Power, D.J., 2016. 'Big brother' can watch us. *Journal of Decision Systems*, 25(1), pp. 578–588.

Premkumar, G. & Rajan, J., 2013. Customer retention in mobile telecom service market in India: Opportunities and challenges. *Ushas Journal of Business Management*, 12(2), pp. 17-29.

Prentice, C. & Nguyen, M., 2020. Engaging and retaining customers with AI and employee service. *Journal of Retailing and Consumer Services*, 56, 102186. https://doi.org/10.1016/j.jretconser.2020.102186

Prentice, C., 2013. Emotional labour and its consequences: the moderating effect of emotional intelligence. In *Individual Sources, Dynamics, and Expressions of Emotion (Research on Emotion in Organisations)*, 9, pp. 187–201.

Prentice, C., 2013b. Service quality perceptions and customer loyalty in casinos. *International Journal of Contemporary Hospitality Management*, 25(1), pp. 49–64. https://doi.org/10.1108/09561111311290219

Prentice, C., Chen, P.-J. & King, B., 2013. Employee performance outcomes and burnout following the presentation-of-self in customer-service contexts. *International Journal of Hospitality Management*, 35, pp. 225–236. https://doi.org/10.1016/j.ijhm.2013.06.007

Prentice, C., Wang, X. and Loureiro, S.M.C., 2019. The influence of brand experience and service quality on customer engagement. *Journal of Retailing and Consumer Services*, *50*, pp.50-59.

Priya, B. & Sharma, V., 2023. Exploring users' adoption intentions of intelligent virtual assistants in financial services: An anthropomorphic and socio-psychological perspectives. *Computers in Human Behavior*, 148, p.107912.

Pusztahelyi, R., 2020. Emotional AI and its challenges in the viewpoint of online marketing. *Curentul Juridic*, 23(2), pp. 13-31.

Qi, J., Wu, F., Li, L. & Shu, H., 2007. Artificial intelligence applications in the telecommunications industry. *Journal of the Operational Research Society*, 58(10), pp. 271–291. doi:10.1111/j.1468-0394.2007.00433.x

Qiu, L. & Benbasat, I., 2009. Evaluating anthropomorphic product recommendation agents: A social relationship perspective to designing information systems. *Journal of Management Information Systems*, 25(4), pp. 145–182.

Qiu, L. & Benbasat, I., 2010. A study of demographic embodiments of product recommendation agents in electronic commerce. *International Journal of Human-Computer Studies*, 68(10), pp. 669–688.

Rafaeli, S. & Noy, A., 2005. Social presence: Influence on bidders in internet auctions. *Electronic Markets*, 15(2), pp. 158–175.

Ralston, K., Chen, Y., Isah, H. & Zulkernine, F., 2019. A voice interactive multilingual student support system using IBM watson. In *Proceedings - 18th IEEE International Conference on Machine Learning and Applications (ICMLA 2019)*, pp. 1924.

Ramachandiran, C.R. & Jomhari, N., 2018. Virtual Agent Design Factors for the 21st Century Learners: A Kansei Approach. In *Proceedings of the 7th International Conference on Kansei Engineering and Emotion Research 2018 (KEER 2018)*, 19-22 March 2018, Kuching, Sarawak, Malaysia, pp. 73-82. Springer Singapore.

Ranaweera, C. & Prabhu, J., 2003. The influence of satisfaction, trust and switching barriers on customer retention in a continuous purchasing setting. *International Journal of Service Industry Management*, 14(4), pp. 374-395.

Ranjbartabar, H. & Richards, D., 2019. Understanding Individual Differences in Users' Preferences and Responses to an Intelligent Virtual Advisor for Reducing Study Stress. *Lecture Notes in Information Systems and Organisation*, p. 227.

Rauschnabel, P.A., Felix, R. & Hinsch, C., 2019. Augmented reality marketing: How mobile AR-apps can improve brands through inspiration. *Journal of Retailing and Consumer Services*, 49, pp. 43–53.

Ravald, A. & Grönroos, C., 1996. The value concept and relationship marketing. *European Journal of Marketing*, 30(2), pp. 19-30.

Raymond, J., 2001. No more shoppus interruptus. *American Demographics*, 23(5), pp. 39–40.

Razek, A.R.A., van Husen, C., Pallot, M. & Richir, S., April 2018. A comparative study on conventional versus immersive service prototyping (VR, AR, MR). In *Proceedings of the Virtual Reality International Conference-Laval Virtual*, pp. 1-10.

Reddy, T., 2017a. Chatbots for customer service will help businesses save $8 billion per year. Retrieved from https://www.ibm.com/blogs/watson/2017/05/chatbots-customer-service-will-help-businesses-save-8-billion-per-year/

Reddy, T., 2017b. How chatbots can help reduce customer service costs by 30%. Retrieved from https://www.ibm.com/blogs/watson/2017/10/how-chatbots-reduce-customer-service-costs-by-30-percent/

Reeves, B. & Nass, C., 1996. *The Media Equation: How People Treat Computers, Television and New Media Like Real People and Places*. Cambridge University Press, New York.

Reichheld, F. & Sasser, E., 1990. Zero defections: Quality comes to services. *Harvard Business Review*, 68(5), pp. 105-111.

Reichheld, F.F. & Kenny, D.W., 1990. The hidden advantages of customer retention. *Journal of Retail Banking*, XII(4), pp. 19-23.

Reinartz, W., Thomas, J.S. & Kumar, V., 2005. Balancing acquisition and retention resources to maximize customer profitability. *Journal of Marketing*, 69(1), pp. 63–79. https://doi.org/10.1509/jmkg.69.1.63.55511

Rodriguez, S.S., Schaffer, J.A., O'Donovan, J. & Höllerer, T., 2019. Knowledge Complacency and Decision Support Systems. In *Proceedings - 2019 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA 2019)*, pp. 43.

Rogers, E.M., 1995. *Diffusion of Innovations*, 4th ed. Free Press.

Rousseau, D.M., Sitkin, S.B., Burt, R.S. & Camerer, C., 1998. Not so different after all: A cross-discipline view of trust. *Academy of Management Review*, 23(3), pp. 393-404. DOI: 10.5465/amr.1998.926617

Russell, S. & Norvig, P., 2020. *Artificial Intelligence: A Modern Approach*, 4th ed. Prentice Hall, NJ.

Rust, R.T. & Huang, M.H., 2014. The Service Revolution and the Transformation of Marketing Science. *Marketing Science*, 33(2), pp. 206-221.

Saad, S.B. & Choura, F., 2022. Online shopping during the Covid-19 crisis: the impact of anthropomorphic virtual agents on consumers' psychological states. *International Journal of Technology Marketing*, 16(1-2), pp. 27-49.

Saari, U.A., Damberg, S., Frömbling, L. & Ringle, C.M., 2021. Sustainable consumption behavior of Europeans: The influence of environmental knowledge and risk perception on environmental concern and behavioral intention. *Ecological Economics*, 189, p. 107155.

Sands, S., Campbell, C., Plangger, K. & Pitt, L., 2022. Buffer bots: The role of virtual service agents in mitigating negative effects when service fails. *Psychology and Marketing*, 39(11), pp. 2039-2054.

Scherer, A., Wünderlich, N.V. & Von Wangenheim, F., 2015. The value of self-service: Long-term effects of technology-based self-service usage on customer retention. *MIS Quarterly*, 39(1), pp. 177-200.

Schneider, D., Klumpe, J., Adam, M. & Benlian, A., 2020. Nudging users into digital service solutions. *Electronic Markets*, 30, pp. 1-19.

Schoorman, F., Mayer, R.C., & Davis, J.H., 2007. An integrative model of organizational trust: Past, present, and future. *Academy of Management Review*, 32(2), pp. 344-354. https://doi.org/10.5465/amr.2007.24348410

Schrage, M. & Kiron, D., August 21, 2018. Improving Strategic Execution With Machine Learning. *MIT Sloan Management Review*. Available at: https://sloanreview.mit.edu/article/improving-strategic-execution-with-machine-learning/

Schrotenboer, D.W., 2019. The Impact of Artificial Intelligence along the Customer Journey: A Systematic Literature Review.

Seo, D., Ranganathan, C. et al., 2008. Two-level model of customer retention in the US mobile telecommunications service market. *Telecommunications Policy*, 32(3-4), pp. 182-196.

Seranmadevi, R. & Senthil Kumar, A., 2019. Experiencing the AI emergence in Indian retail – Early adopters approach. *Management Science Letters*, 9, pp. 33-42. https://doi.org/10.5267/j.msl.2018.11.002

Seymour, M., Yuan, L., Dennis, A. & Riemer, K., 2019. Crossing the Uncanny Valley? Understanding Affinity, Trustworthiness, and Preference for More Realistic Virtual Humans in Immersive Environments. In *Proceedings of the Hawaii International Conference on System Sciences (HICSS)*.

Sha, S., Nazim, M., & Rajeswari, M., February 22, 2019. Creating a Brand Value and Consumer Satisfaction in E-Commerce Business Using Artificial Intelligence. In *Proceedings of International Conference on Sustainable Computing in Science, Technology and Management (SUSCOM)*, Amity University Rajasthan, Jaipur - India. Available at SSRN: https://ssrn.com/abstract=3351618

Shevat, A., 2017. *Designing Bots: Creating Conversational Experiences*. O'Reilly Media, UK.

Short, J., Williams, E. & Christie, B., 1976. *The Social Psychology of Telecommunications*.

Siddiqui, M.A., 2023. The significance of AI enhanced customer feedback for providing insights on customer retention and engagement strategies for mobile companies. *International Journal Of Engineering And Management Research*, *13*(6), pp.182-206.

Simester, D., Timoshenko, A. & Zoumpoulis, S.I., 2020. Targeting prospective customers: Robustness of machine-learning methods to typical data challenges. *Management Science*, 66(6), pp. 2495–2522. https://doi.org/10.1287/mnsc.2019.3308

Simmons, R., Makatchev, M., Kirby, R., Lee, M.K., Fanaswala, I., Browning, B. et al., 2011. Believable robot characters. *AI Magazine*, 32(4), pp. 39–52.

Simon, H.A., 1990. Invariants of human behavior. *Annual Review of Psychology*, 41(1), pp. 1–20.

Simonsohn, U. & Ariely, D., 2008. When rational sellers face nonrational buyers: evidence from herding on eBay. *Management Science*, 54(9), pp. 1624-1637.

Slim, B.M.M., Marion, G. & Ingrid, P., 2013. Improving consumer performance and perceived service quality in a new type of commercial environment in 3D, thanks to embodied virtual sales agents. In *E-Marketing in Developed and Developing Countries: Emerging Practices*, pp. 233-245.

Smidt, F. & Power, B., 2020. 8 ways consumers across Europe adapted their shopping behaviour this year. Think with Google. Available at: https://www.thinkwithgoogle.com/intl/en-cee/insights-trends/industry-perspectives/consumers-adapted-shopping-behaviour-covid/

Snyder, M. & Cunningham, M.R., 1975. To comply or not comply: Testing the self-perception explanation of the foot-in-the-door phenomenon. *Journal of Personality and Social Psychology*, 31(1), pp. 64–67.

Söderlund, M. & Oikarinen, E.-L., 2021. Service encounters with virtual agents: an examination of perceived humanness as a source of customer satisfaction. *European Journal of Marketing*, 55(13), pp. 94-121.

Soderlund, M., Oikarinen, E.-L. & Tan, T.M., 2021. The happy virtual agent and its impact on the human customer in the service encounter. *Journal of Retailing and Consumer Services*, 59.

Söderlund, M., Oikarinen, E.-L. & Tan, T.M., 2022. The hard-working virtual agent in the service encounter boosts customer satisfaction. *International Review of Retail, Distribution and Consumer Research*, 32(4), pp. 388-404.

Solomon, M., 2006. *Consumer Behavior*. 1st ed. Harlow, England: Financial Times/Prentice Hall.

Song, Y.W., 2019. User acceptance of an artificial intelligence (AI) virtual assistant: an extension of the technology acceptance model. Doctoral dissertation.

Song, Y.W., 2019. User acceptance of an artificial intelligence (AI) virtual assistant: an extension of the technology acceptance model (Doctoral dissertation).

Steichen, D. & Terrien, C., 2009. A model of demand in a repeated purchase situation: A simulation of the Champagne wine market. *International Journal of Wine Business Research*, 21(4), pp. 354-372.

Steichen, D. & Terrien, C., 2009. A model of demand in a repeated purchase situation: A simulation of the Champagne wine market. *International Journal of Wine Business Research,* 21(4), pp. 354-372.

Sujata, J., Abhijit, C. & Yatin, J., 2015. Influence of brand-oriented factors on consumer loyalty of prepaid mobile services. *Indian Journal of Science and Technology*.

Sujata, J., Abhijit, C. & Yatin, J., 2015. Influence of brand-oriented factors on consumer loyalty of prepaid mobile services. *Indian Journal of Science and Technology*, India.

Sumangala, D., 2013. New strategies of industrial organization: outsourcing and consolidation in the mobile telecom sector in India. Ambedkar University.

Sumangala, D., 2013. New strategies of industrial organization: outsourcing and consolidation in the mobile telecom sector in India. *Ambedkar University*.

Svennevig, J., 2000. Getting acquainted in conversation: A study of initial interactions. Philadelphia: John Benjamins Publishing.

Svennevig, J., 2000. *Getting Acquainted in Conversation: A Study of Initial Interactions*. Philadelphia: John Benjamins Publishing.

Swanson, S.R. & Hsu, M.K., 2009. Critical incidents in tourism: failure, recovery, customer switching, and word-of-mouth behaviors. *Journal of Travel & Tourism Marketing*, 26(2), pp. 180-194.

Swanson, S.R. & Hsu, M.K., 2009. Critical incidents in tourism: failure, recovery, customer switching, and word-of-mouth behaviors. *Journal of Travel & Tourism Marketing*, 26(2), pp. 180-194.

Syam, N. & Sharma, A., 2018. Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, pp. 135-146.

Syam, N. & Sharma, A., 2018. Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management*, pp. 135-146.

Techlabs, M., 2017. Can chatbots help reduce customer service costs by 30%? *Chatbots Magazine*. Available at: https://chatbotsmagazine.com/how-with-the-help-of-chatbots-customer-service-costs-could-be-reduced-up-to-30-b9266a369945

Teddlie, C. & Tashakkori, A., 2003. Major issues and controversies in the use of mixed methods in the social and behavioral sciences. In *Handbook of Mixed Methods in Social & Behavioral Research*, p. 3.

Teddlie, C. & Tashakkori, A., 2003. Major issues and controversies in the use of mixed methods in the social and behavioral sciences. In *Handbook of Mixed Methods in Social & Behavioral Research*, pp. 3.

Tezcan, T. & Zhang, J., 2014. Routing and staffing in customer service chat systems with impatient customers. *Operations Research*, 62(4), pp. 943-956. https://doi.org/10.1287/opre.2014.1284

Thatcher, J.B., Carter, M., Li, X. & Rong, G., 2013. A Classification and Investigation of Trustees in B-to-C e-Commerce: General vs. Specific Trust. *Communications of the Association for Information Systems*, 32(4). https://doi.org/10.17705/1CAIS.03204

Times, H., 2014. Indian smartphone companies take on global giants. *Hindustan Times*. Available at: http://www.hindustantimes.com/business-news/indian-smartphone-cos-challenging-big-players-like-apple-samsung/article1-1131631.aspx

Trendone, 2016. Futuregram. Available at: http://futuregram.trendone.com

Tripathi, S. & Verma, S., 2018. Social media, an emerging platform for relationship building: A study of engagement with nongovernment organizations in India. *International Journal of Nonprofit and Voluntary Sector Marketing*, 23(1), e1589. https://doi.org/10.1002/nvsm.1589

Turnbull, P.W., Leek, S. et al., 2000. Customer Confusion: The Mobile Phone Market. *Journal of Marketing Management*, 16(1-3), pp. 143-163.

Twyman, N.W., Pentland, S.J. & Spitzley, L., 2020. Design Principles for Signal Detection in Modern Job Application Systems: Identifying Fabricated Qualifications. *Journal of Management Information Systems*, 37(3), pp. 849-874.

Ugaz, M. & Alva, A.B., 2015. Model for effective collaborative learning in virtual worlds with intelligent agents. In *Social Media and Networking: Concepts, Methodologies, Tools, and Applications*, pp. 807-829.

Unity Developers, 2021. 2021 is a Year of a Substantial Rise of AR and VR Apps. Retrieved from https://unitydevelopers.co.uk/2021-is-a-year-of-a-substantial-rise-of-ar-and-vr-apps/ on July 24, 2021.

Upadhyay, N., Kamble, A. & Navare, A., 2023. Virtual healthcare in the new normal: Indian healthcare consumers adoption of electronic government telemedicine service. *Government Information Quarterly*, 40(2), p. 101800.

Urman, A., Makhortykh, M. & Ulloa, R., 2022. Auditing the representation of migrants in image web search results. *Humanities and Social Sciences Communications*, 9(1).

US Bureau of Labor Statistics, 2020. Advertising, Promotions, and Marketing Managers: Occupational Outlook Handbook. Retrieved from https://www.bls.gov/ooh/management/advertising-promotions-and-marketing-managers.htm on September 1, 2020.

Vada, S., Prentice, C. & Hsiao, A., 2019. The influence of tourism experience and wellbeing on place attachment. *Journal of Retailing and Consumer Services*, 47, pp. 322–330. https://doi.org/10.1016/j.jretconser.2018.12.007

Valls, A., Gibert, K., Orellana, A. & Antón-Clavé, S., 2018. Using ontology-based clustering to understand the push and pull factors for British tourists visiting a Mediterranean coastal destination. *Information & Management*, 55(2), pp. 145–159. https://doi.org/10.1016/j.im.2017.05.002

van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P. & Verhoef, P.C., 2010. Customer engagement behavior: Theoretical foundations and research directions. *Journal of Service Research*, 13(3), pp. 253–266. https://doi.org/10.1177/1094670510375599

van Esch, P., Arli, D., Gheshlaghi, M.H., Andonopoulos, V., von der Heidt, T. & Northey, G., 2019. Anthropomorphism and augmented reality in the retail environment. *Journal of Retailing and Consumer Services*, 49, pp. 35–42.

van Pinxteren, M.M.E., Pluymaekers, M., Lemmink, J. & Krispin, A., 2023. Effects of communication style on relational outcomes in interactions between customers and embodied conversational agents. *Psychology and Marketing*, 40(5), pp. 938-953.

Verhagen, T., Van Nes, J., Feldberg, F. & Van Dolen, W., 2014. Virtual customer service agents: Using social presence and personalization to shape online service encounters. *Journal of Computer-Mediated Communication*, 19(3), pp. 529–545.

Violet, G., Malcolm, R., Sailee, S., Shwaitang & T., Renny, 2020. Reimagining customer engagement for the AI bank of the future. McKinsey & Company. Available at: https://www.mckinsey.com/industries/financial-services/our-insights/reimagining-customer-engagement-for-the-ai-bank-of-the-future

Walter, Z. & Lopez, M.S., 2008. Physician acceptance of information technologies: Role of perceived threat to professional autonomy. *Decision Support Systems*, 46(1), pp. 206-215.

Wang, D., Han, H., Zhan, Z., Xu, J., Liu, Q. & Ren, G., 2015. A problem solving oriented intelligent tutoring system to improve students' acquisition of basic computer skills. *Computers & Education*, 81, pp. 102-112. https://doi.org/10.1016/j.compedu.2014.10.003

Wang, D., Richards, D., Bilgin, A.A. & Chen, C., 2022. The development of open government data: Connecting supply and demand through portals. In *The Development of Open Government Data: Connecting Supply and Demand Through Portals*, pp. 1-342.

Warwick, K. & Shah, H., 2016. A brief introduction to artificial intelligence. In *Turing's Imitation Game* (pp. 41–55). Cambridge University Press.

Watson, H.J., 2017. Preparing for the cognitive generation of decision support. *MIS Quarterly Executive*, 16(3), pp. 153–169.

Wedel, M., Bigné, E. & Zhang, J., 2020. Virtual and augmented reality: Advancing research in consumer marketing. *International Journal of Research in Marketing*, 37(3), pp. 443–465.

Weiner, B., 1985. Spontaneous causal thinking. *Psychological Bulletin*, 97(1), pp. 74–84.

Weizenbaum, J., 1966. ELIZA—A computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1), pp. 36–45.

Wessel, M., Adam, M. & Benlian, A., 2019. The impact of sold-out early birds on option selection in reward-based crowdfunding. *Decision Support Systems*, 117, pp. 48–61.

Whatley, M.A., Webster, J.M., Smith, R.H. & Rhodes, A., 1999. The effect of a favor on public and private compliance: How internalized is the norm of reciprocity? *Basic and Applied Social Psychology*, 21(3), pp. 251–259.

Wieseke, J., Geigenmüller, A. & Kraus, F., 2012. On the role of empathy in customer-employee interactions. *Journal of Service Research*, 15(3), pp. 316–331.

Wilkinson, N. & Klaes, M., 2012. *An Introduction to Behavioral Economics*, 2nd ed. New York: Palgrave Macmillan.

Wirth, N., 2018. Hello marketing, what can artificial intelligence help you with? *International Journal of Market Research*, 60(5), pp. 435–438. https://doi.org/10.1177/1470785318776841

Wirtz, J., den Ambtman, A., Bloemer, J., Horváth, C., Ramaseshan, B., van de Klundert, J., Gurhan Canli, Z. & Kandampully, J., 2013. Managing brands and customer engagement in online brand communities. *Journal of Service Management*, 24(3), pp. 223–244. https://doi.org/10.1108/09564231311326978

Wirtz, J., Patterson, P.G., Kunz, W.H., Gruber, T., Lu, V.N., Paluch, S. & Martins, A., 2018. Brave new world: service robots in the frontline. *Journal of Service Management*, 29(5), pp. 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Wutz, M., Hermes, M., Winter, V. & 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, e46548.

Xavier, R. & Pereira, F.C., 2017. Internet marketing and the Portuguese marketplace. In *Impact of E-commerce on Consumers and Small Firms*. Routledge, pp. 123-138.

Xiang, Z., Schwartz, Z., Gerdes, J.H. & Uysal, M., 2015. What can big data and text analytics tell us about hotel guest experience and satisfaction? *International Journal of Hospitality Management*, 44, pp. 120–130. https://doi.org/10.1016/j.ijhm.2014.10.013

Xu, K. & Lombard, M., 2017. Persuasive computing: Feeling peer pressure from multiple computer agents. *Computers in Human Behavior*, 74, pp. 152–162.

Yamuna, S.M. & Shiji, R., 2017. Smart Phone Users Brand Awareness Towards 4g Mobile Phone Services (a Study With Special Reference To Coimbatore City). *Indian Journal of Applied Research*, 6(2). Available at: https://www.worldwidejournals.com/paripex/article/smart-phone-users-brand-awareness-towards-4g-mobile-phone-services-a-study-with-special-reference-to-coimbatore-city/MzQzMDk=/?is=1

Yao, M., 2018. 11 Powerful AI Tools You Can Use To Upgrade Your Customer Experience. Available at: https://www.topbots.com/best-customer-service-automation-enterprise-technology-software/

Yaoyuneyong, G., Foster, J., Johnson, E. & Johnson, D., 2016. Augmented reality marketing: Consumer preferences and attitudes toward hypermedia print ads. *Journal of Interactive Advertising*, 16(1), pp. 16–30.

Yau, K.-L. A., Saad, N. M. & Chong, Y.-W., 2021. Artificial intelligence marketing (AIM) for enhancing customer relationships. *Applied Sciences (Basel, Switzerland)*, 11(18), p. 8562. https://doi.org/10.3390/app11188562

Yoo, H., Kwon, O. & Lee, N., 2016. Human likeness: cognitive and affective factors affecting adoption of robot-assisted learning systems. *New Review of Hypermedia and Multimedia*, 22(3), pp. 169-188.

Zaichkowsky, J.L., 1985. Measuring the involvement construct. *Journal of Consumer Research*, 12(3), pp. 341–352.

Zhang, H., Lu, Y., Shi, X., Tang, Z. & Zhao, Z., 2012. Mood and social presence on consumer purchase behaviour in C2C E-commerce in Chinese culture. *Electronic Markets*, 22(3), pp. 143–154.

Zojaji, S., Peters, C. & Pelachaud, C., October 2020. Influence of virtual agent politeness behaviors on how users join small conversational groups. In *Proceedings of the 20th ACM International Conference on Intelligent Virtual Agents*, pp. 1-8.

Zumstein, D. & Hundertmark, S., 2017. Chatbots – An Interactive Technology for Personalized Communication, Transactions and Services. *IADIS International Journal on WWW/Internet,* 15, pp. 96-109.

## Annexure I - Questionnaire

### Demographics

1. Place
   a) India
   b) US
   c) EMEA
   d) APAC
2. Gender
   a) Male
   b) Female
3. Age
   a) 18-30 years
   b) 30-40 years
   c) 40-50 years
   d) Above 50 years
4. Firm Age
   a) Less than or equal to 25 years
   b) More than 25 years
5. Technology Adoption
   a) High
   b) Low
6. R&D Investment
   a) High
   b) Low

***Please rate the Below Statements***

*(From 1 – strongly disagree to 7 – strongly agree)*

| Construct | Indicator | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| Performance Expectancy *(Venkatesh et al., 2012)* | PE01 - I find virtual agents useful in our line of work | | | | | | | |
| | PE02 - Using virtual agents will increase efficiency on the job | | | | | | | |
| | PEO3 - Using virtual agents will increase job productivity | | | | | | | |
| | PE04 – Conversational Virtual Agents would improve the overall customer experience | | | | | | | |
| Effort Expectancy *(Venkatesh et al., 2012)* | EE01 – Virtual agents provide accurate context and summarization to continue customer service and interaction | | | | | | | |
| | EE02 - Handover and assistance from Virtual agent is smooth and understandable to carry on with the customer interaction | | | | | | | |
| | EE03 - I find virtual agents easy to use | | | | | | | |
| Facilitating Condition | FC01 - I have the necessary resources to use/implement virtual agents | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *(Venkatesh et al., 2012)* | FC02 – I/My team have the knowledge necessary to use/adopt virtual agents | | | | | | | |
| | FC03 – My company/business unit facilitates the use of virtual agents through various supporting initiatives | | | | | | | |
| | FC04 – I am aware of CHATGPT/Generative AI technologies advancement in Virtual Agents | | | | | | | |
| | FC05 – I have gone through training/facilitation on Generative AI/CHAT-GPT | | | | | | | |
| Social Influence *(Venkatesh et al., 2012)* | SI01 - Peers who influence my behavior think that I should use virtual agents. | | | | | | | |
| | SI02 – My peers who use virtual agents have a more positive attitude towards the use of virtual agents in their job. | | | | | | | |
| | SI03 - People who are important to me think that I should use virtual agents. | | | | | | | |
| Perceived Susceptibility | PS01 – There is a high probability that virtual agents can cause security breaches. | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *(Liang & Xue, 2009)* | PSO2 – It is likely that the use of virtual agents will lead to misinformation. | | | | | | | |
| | PSO3 – It is plausible that virtual agents might fail to effectively service clients. | | | | | | | |
| | PS04 - Use of Virtual Agents would risk the reputation of the business | | | | | | | |
| Perceived Severity *(Liang & Xue, 2009)* | PSE01 – If a security breach occurred through a virtual agent, the consequences would be severe. | | | | | | | |
| | PSE02 – Misinformation from virtual agents could have serious repercussions for my job. | | | | | | | |
| | PSE03 – Failure of virtual agents to effectively service clients can have grave implications for the company. | | | | | | | |
| Perceived Threat *(Liang & Xue, 2009)* | PT01 – I am worried that virtual agents might increase the risk to my job security. | | | | | | | |
| | PT02 – I am concerned about the potential threats that virtual agents can bring to our existing systems. | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | PT03 – I perceive the adoption of virtual agents as a threat to the quality of service. | | | | | | | |
| Adoption Intention *(Venkatesh et al., 2012)* | IU01 – Given the opportunity, I plan to use virtual agents in my tasks. | | | | | | | |
| | IU02 – I am willing to integrate virtual agents into my existing workflow | | | | | | | |
| | IU03 – I could envision adopting virtual agents as a long-term tool for my role. | | | | | | | |