RELATIONSHIP MARKETING AFFECTING THE CUSTOMER EXPERIENCE IN USING AI-CHATBOT

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BY

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DECLARATION

I hereby declare that:

(1) This undergraduate FYP is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.

(2) No portion of this FYP has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.

(3) Sole contribution has been made by me in completing the FYP.

(4) The word count of this research report is 12938 words.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
NLP	Natural Language Processing
SOR	Stimulus-organism-response
S	Stimulus
O	Organism
R	Response
SEMs	Strategic Experiential Modules
PLS-SEM	Partial Least Squares Structural Equation Modelling
CR	Composite Reliability
SQ	Service Quality
SE	Security
TR	Trust
GO	Grounding
CE	Customer Experience
AVE	Average Variance Extracted
HTMT	Heterotrait-monotrait
VIF	Variance Inflation Factor
CFA	Confirmatory Factor Analysis

PREFACE

Artificial intelligence (AI) is becoming more and more integrated into many industries, which has completely changed how companies run. In fields including academics, healthcare, and beauty, AI-Chatbots have become one of the most effective AI applications, offering efficiency and convenience. AI-Chatbots can help businesses cut expenses, increase efficiency, and decrease mistakes.

However, despite these advancements, there is a noticeable lack of research on relationship marketing affecting customer experience in using AI-Chatbots. This gap inspired me to explore how AI-Chatbot affects customer experience in this context. I aim to identify the factors that shape customer experience with AI-Chatbots and provide insights that businesses can leverage to optimize their strategies.

I started by studying the foundations of artificial intelligence and its uses before progressively focusing on AI-Chatbots to conduct this research. I seek to guarantee the correctness and applicability of my conclusions by carefully examining trustworthy and pertinent sources. Under the direction of my supervisor, I wrote this project with the goal of making a significant contribution to a field of research that has not received enough attention.

ABSTRACT

Artificial intelligence (AI) chatbots are becoming a major corporate customer-facing tool that can lower costs and improve customer service efficiency. The way customers communicate with one another is being revolutionized by AI-Chatbot. Empirical studies on customer experiences facilitated by AI-Chatbot are scarce. Few studies have attempted to evaluate the security and quality of services that AI chatbots offer to users. To anticipate customer trust and grounding leads to impact customers' experience, this study applies service quality and security by integrating AI-Chatbot's characteristics. The objective of the research is to investigate the factors affecting customer experience in using AI-Chatbot while considering the mediating roles of trust and grounding. The theoretical model put out in this study is based on the SOR model, customer experience theory, and service quality theory. Data was gathered from 385 consumers who answered online surveys about their experiences with AI-Chatbot. The total number of valid responses is 334. The methodology was covered by analyzing 334 responses using partial least squares-structural equation modeling. The results show how important trust and grounding mediate between the AI-Chatbot's service quality, security and customer experience. As a result, the customer's trust and grounding greatly impact customer experience. Thus, all the constructs are valid and reliable. Through the proposal and evaluation of AI-Chatbot's service quality and security, this work makes theoretical and practical contributions. Retailers, business, and technology developers using AI-Chatbots in general industry to serve their customers can also benefit from the study's practical consequences. This study has theoretical implications by extending the stimulus-organism-response (SOR) framework. Limitations of the study include the lack of diverse demographics, perspectives, and other limitations. Future research could be conducted from different demographics and perspectives.

Keyword: AI-Chatbot, Security, Trust, Grounding, Customer Experience

CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

The research background, research problem, research objectives, research questions, and significance of the study are the five sections that make up this chapter.

1.1 Research Background

The way that businesses engage with their customers could be completely transformed by the introduction of artificial intelligence (AI) (McLean & Osei-Frimpong, 2019). Artificial intelligence differs from human intelligence through its rapid data processing, transforming data into information to guide goal-oriented behavior (Paschen, Kietzmann, & Kietzmann, 2019). AI is the term used to describe computers, systems, algorithms, or programs that display intelligence (Shankar, 2018). Conversational agents are becoming one of the most promising applications of artificial intelligence in the context of digital marketing and online shopping (Yang et al., 2021).

Businesses are increasingly implementing AI technology backed by data analytics to enhance customer-brand interactions in response to pressure on margins, faster strategy cycles, and higher customer expectations. The entire customer experience is improved by AI developments, which offer better insights into consumer preferences and buying patterns (Evans, 2019). AI-enabled services could be included into a marketing plan aimed at increasing client engagement and loyalty to improve operational efficiency and expedite interactions (Kronemann, 2022; Nguyen et al., 2021; Prentice & Nguyen, 2020).
With more than 100,000 chatbots developed on Facebook Messenger since 2017, people have been interacting with AI chatbots on social media and messaging apps

more often (Araujo, 2018). Chatbots are currently used in a variety of industries, including marketing (17%), support (37%) and sales (41%) (Misischia et al., 2022). By 2020, 85% of customer service interactions will be managed by automated systems instead of human customer service representatives (Gartner,2016). By 2024, the market for AI-Chatbots and associated technologies is predicted to surpass $1.34 billion. 95% of customer service interactions are predicted to be assisted by technology by 2025. (Crolic et al., 2022).

AI-Chatbot is a software tool that interacts with humans by synthesising voice or text to resemble human conversation for amusement or information retrieval (Dahiya, 2017). The first AI-Chatbots were developed in 1966 (Güzeldere & Franchi, 1995), but their application was restricted by hardware and network limitations. Advancements in AI and natural language processing (NLP) have enabled AI-Chatbots to engage in more complex discussions, expanding their use in e-commerce, including financial consultations and customer support (Heo & Lee, 2018).

With the use of sophisticated language models, AI -Chatbots such as ChatGPT converse with customers in natural language while transforming inputs into responses that are pertinent to the context and coherent (Dilmaghani, 2023; Følstad et al., 2018). AI, NLP, and machine learning technologies are used in AI-Chatbots, which are computer programmes that simulate human speech (Adamopoulou & Moussiades, 2020).

AI-Chatbots, such as Alexa and message bots, are frequently utilized for customer support on e-commerce websites and applications. Natural communication is a crucial component of landing pages, which are used to engage with customers and offer solutions (Doorn et al., 2017; Sheehan et al., 2020). Therefore, the service quality of AI-Chatbot will enhance customer experience.

The use of AI technology and the need for ever-increasing amounts of data may compound customers' lack of trust (Dwivedi et al., 2019). Customers may feel a less satisfactory experience if there is no human interaction or if additional work is needed. For AI-powered consumer experiences, better understanding is required

(Ameen et al., 2021). Thus, Customer trust, grounding, experience are influenced by AI-Chatbot components such tangibles, reliability, responsiveness, assurance, and empathy. The impact they have on the customer experience will be investigated in this study.

1.2 Research Problem

There are many studies on the quality of interpersonal services in the body of current research (Prentice & Kadan, 2019; Scheidt & Chung, 2019; Suhartanto et al., 2019), however there are still lacking studies on how users react to automated services, particularly those with artificial intelligence (AI) (Prentice, Lopes, & Wang, 2020) specifically AI-Chatbot. Although AI-Chatbots have great potential for e-retailing, barriers such as a lack of context awareness and design experience prevent their widespread use. A comprehensive investigation into the factors that genuinely enhance chatbot functionality with customers is lacking (Przegalinska et al., 2019). Thus, this research investigates the relationship between the service quality and customer experience.

There is research to describes from the viewpoint of the customer, the essential success criteria for AI-enabled customer experiences (Ameen et al., 2021). However, it is lacking on investigate the security of AI technology from a customer perspective. As AI-Chatbots get smarter and more powerful, new kinds of attacks that take advantage of vulnerabilities could appear. According to ET CISO (2024), sensitive client health information was made public on Telegram chatbots in September 2024 due to a major breach at the insurance company Star Health. Addressing emerging risks requires ongoing study and development. AI-Chatbots depend on information security, which offers a chance to investigate how security affects the user experience.

The preservation of user trust and data protection is an important aspect to AI-Chatbots' success and broad use (Yang et al., 2023). AI-Chatbots’ service quality and security in safeguarding data and privacy determines customer trust. Following the idea of least collaborative effort, people should try to ground with as little cooperative effort as possible. But depending on the communication route, the amount of work needed changes significantly (Clark & Brennan, 1991). Good service quality and a protective AI-Chatbot affect the customer's effort to ground with the AI-Chatbot as it serves as a communication medium.

1.3 Research Objectives

1.3.1 General Objective

The objective of this study is to examine the factors influencing the customer's experience of AI-Chatbots while taking grounding and trust into account as mediating elements.

1.3.2 Specific Objectives

RO1: To investigate the relationship between service quality and trust.

RO2: To investigate the relationship between service quality and grounding.

RO3: To investigate the relationship between security and trust.

RO4: To investigate the relationship between security and grounding.

RO5: To investigate the relationship between trust and customer experience.

RO6: To investigate the relationship between grounding and customer experience.

RO7: To investigate trust mediates the relationship between service quality and customer experience.

RO8: To investigate trust mediates the relationship between security and customer experience.

RO9: To investigate grounding mediates the relationship between service quality and customer experience.

RO10: To investigate grounding mediates the relationship between security and customer experience.

1.4 Research Questions

RQ1: What is the relationship between service quality and trust?

RQ2: What is the relationship between service quality and grounding?

RQ3: What is the relationship between security and trust?

RQ4: What is the relationship between security and grounding?

RQ5: What is the relationship between trust and customer experience?

RQ6: What is the relationship between grounding and customer experience?

RQ7: What is the relationship between service quality and customer experience mediated by trust?

RQ8: What is the relationship between security and customer experience mediated by trust?

RQ9: What is the relationship between service quality and customer experience mediated by grounding?

RQ10: What is the relationship between security and customer experience mediated by grounding?

1.5 Research Significance

This research is significant because it examines how AI-Chatbots powered by artificial intelligence will impact the customer experience soon. With the aid of AI technology, customers can now plan their shopping activities (Kunz et al., 2019), practitioners of management and marketing are presented with both new difficulties and opportunities (Haenlein & Kaplan, 2019). Through this research, they better evaluate customers' experience in using AI-Chatbot. Young customers have higher expectations for "nowness" and customisation, so marketers must ensure their AI systems can fulfil and meet this demand (Chattaraman et al. 2019). To meet consumer expectations, marketers can use this research to evaluate the aspects that affect the customer experience with AI-Chatbots.

To improve and expand customer experiences, marketing managers must experiment with the application of novel tools and strategies, like AI-driven service (Crolic et al. 2022). By preventing poor service quality and security issues that impact the customer experience, this research assists marketing managers in making successful use of AI-Chatbots. It evaluates the efficacy and long-term sustainability of AI-Chatbots in customer service while tackling sociological and economic issues for economic practitioners. With its foundation in SOR theory, it investigates how customer trust and grounding are affected by the AI-Chatbot's service quality and security, effect on their experience, giving scholars a better knowledge of how customers behave.

1.6 Conclusion

This chapter focuses on the problem regarding customer experience in using AI-Chatbot. At chapter 2 present review of past studies to understand factors affecting the customer experience in using AI-Chatbot.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

To understand customer experience in using AI-Chatbot, the stimulus-oragnism-response (SOR) model is applied to investigate the service quality and security of AI-Chatbot affect the trust and grounding of customer.

2.1 Underlying Theory

It was originally created that the "stimulus-organism-response framework" by Mehrabian & Russell (Cheng et al., 2021) and then modified by Jacoby (2002). According to the SOR framework, people will respond and behave in particular ways depending on the circumstances (Kamboj et al., 2018). There are two main types of reaction behaviours that people exhibit: those that involve positive actions, like exploring and affiliate, and those that involve negative actions, like wanting to react negatively (Kim et al., 2020). The SOR framework has been expanded upon by previous research to include a variety of domains, including online shopping (Eroglu et al.,2003), experience with websites (Mollen & Wilson, 2010), retail industry customer behaviour (Rose et al., 2012) and the travel and tourism sector (Kim et al.,2020).

SOR theory, a psychological theory for analysing consumer behaviour, has been used extensively in e-commerce (Fiore & Kim, 2007; Chang et al., 2011; Wu & Li, 2018). For instance, Eroglu et al. (2003) contended that the virtual platform's ambient or atmospheric cues (S-stimuli) have the potential to impact users' emotions or cognition (O-organism), subsequently influencing their behavioural results (R-response). The SOR framework is used in this study to describe how customers behave and interpret information when interacting with an online store's text-based chatbot. According to the S-O-R paradigm, observable behavioural responses are the consequence of internal organismic reactions triggered by external stimuli (Cheng et al., 2022). An AI-Chatbot's responsiveness, accuracy, speed, and helpfulness are examples of its external stimulus (S). Its overall service quality is its primary focus. Trust between AI-Chatbot users is seen as an internal organism (O) that symbolises a person's emotional and mental condition, or what is known as their "organism". The ultimate behavioral reaction is consumer e-brand loyalty (R) which shows how much a customer's interactions with the AI-Chatbot have influenced their online brand loyalty (Shahzad et al., 2024).

2.2 Review of Literature

2.2.1 Service Quality

The definition of service quality is a customer's subjective assessment of the service throughout its interactive delivery process (Dabholkar et al., 2000; Parasuraman et al., 1988). The expectancy disconfirmation theory serves as the foundation for this conceptualization of service quality (Collier & Bienstock, 2006), where the results of the evaluation of service quality are determined by comparing the perceived quality of the service received with pre-existing expectations of what that service should give (Choi, Lee, Lee, & Subramani, 2004). It was suggested that customer perceived value and satisfaction are influenced by the quality of information, system, and service on a website, which greatly impacts their service experience (Wang et al., 2016).

Furthermore, SERVQUAL (Service Quality) and SERVPERF (Service Performance) are the two primary tools frequently used to measure the service quality of AI-Chatbot. Whereas SERVPERF concentrates exclusively on customer perceptions, SERVQUAL addresses both the expectations and perceptions of customers' evaluations. When it comes to predicting overall service quality, SERVQUAL and SERVPERF are equally reliable (Thanh et al., 2023). While SERVPERF is advised due to its strong theoretical model, SERVQUAL is thought to be helpful for diagnostic purposes (Carrillat et al., 2007).

The SERVPERF model was developed by Cronin and Taylor, 22 items in the model that span five dimensions: assurance, empathy, responsiveness, tangibles, and reliability (Cronin & Taylor, 1992).

The service quality's concept has multiple dimensions (Korfiatis et al., 2019). Researchers have looked at SERVQUAL, one of the most widely used measures for assessing service quality, in a variety of contexts (Parasuraman et al., 1988). Numerous offline and online contexts have made extensive use of this scale (Jiang et al., 2002; O'Neill et al., 2001).

The SERVQUAL model, which is helpful for diagnostic purposes, is used in this study to measure service quality (Carrillat et al., 2007). It has five dimensions are tangibles, reliability, responsiveness, assurance, and empathy.

According to Parasuraman et al. (1998), physical facilities, tools, and personnel appearances are considered tangibles, while the ability to provide the promised service accurately and consistently is referred to as reliability. On the other hand, the willingness to help customers by offering immediate assistance is referred to as responsiveness. Assurance is the ability of the employees to inspire confidence and trust as well as their knowledge and politeness includes the dimensions of understanding, access, communication, competence, security, and credibility (Meyer-Waarden et al., 2020). The AI-Chatbot' s service quality refers to credibility to give customers assurance and inspire their confidence and trust. Next, Empathy refers to a company's thoughtful, individualized attention to its customers.

2.2.2 Security

Concerning the security and privacy of users' private information are raised by the fact that as these systems proliferate, their susceptibility to security threats and attacks also increases (Adamopoulou & Moussiades, 2020). Users face the danger of having their data misused, accessed without authorization, or compromised, which emphasizes how crucial it is to handle privacy issues for both data security and consumer trust (Gumusel et al., 2024).

If users don't know how their data is being used or who can access it, they might feel uneasy by sharing private information with AI-Chatbots. The collection, storing, and use of data by AI-Chatbots must all be transparent to developers. To mitigate security concerns with AI-Chatbots, developers can employ blockchain technology and end-to-end encryption to safeguard user data, guaranteeing its availability, confidentiality, and integrity (Yang et al., 2023).

Developers can also apply organisational, managerial, and technical controls. This includes training staff members and users in security awareness, enforcing access controls, and performing routine security assessments. Additionally, users are taught data security procedures and are motivated to properly safeguard their personal data through security awareness training (Yang et al., 2023).

Security audits are crucial because they independently confirm that ChatGPT follows its privacy and security guidelines. Although security is of utmost importance to OpenAI, there is a dearth of information available about the datasets utilised to train ChatGPT, how its algorithm and AI model operate, the details of data storage, access and usage protocols, and the sharing of data with unauthorised parties. Security audits evaluate security and privacy procedures after the fact. AI-Chatbot must provide users with the option to request an audit trail that shows when, by whom, and for what reason their personal information was accessed for users to feel comfortable trusting its security and privacy claims (Li, 2015).

2.2.3 Trust

Meanwhile, the customer's faith in the calibre and reliability of the company's services is define as trust (Garbarino & Johnson, 1999). As AI systems grow more complex and self-governing, trust is essential to their broad adoption and integration (Paliszkiewicz & Goluchowski, 2024). The psychological process of building trust refers to lower uncertainty and boost the possibility of fruitful interactions with external entities (Lukyanenko, Maass & Storey, 2022; Venger & Dozortsev, 2023).

Moreover, trust and the overall perception that customers have of a service are greatly influenced by reliability. As seen via the human factor, reliability is essential to service quality. According to this study, responsiveness has a lesser impact on customer satisfaction than empathy and dependability. Reliable service, individualized attention, timely delivery, and trust-building are how these elements are attained (Johnson & Karlay, 2018).

In the relationship between humans and technology, trust can be put in the technology or the technology's supplier (Siau & Wang 2018), which may impact on how individuals use technology (Kronemann, 2022). Trust will improve acceptance and reduce reactive behaviour.

Transparency and disclosure are obviously necessary, but when examining the implications of AI, trust is still a crucial factor to consider (Kronemann, 2022).

By utilizing AI-Chatbots for targeted, interactive, and engaging marketing, businesses may improve their relationship with the public while increasing brand loyalty, communication, and trust (Chanda, 2024).

The success of automated services depends on trust, as it establishes the parameters of the interaction between humans and automation (Hengstler, Enkel, & Duelli, 2016). As customers want to maintain control over how retailers use their data, privacy is an essential component of trust (Wang et al., 2019). Prior research has shown that trust can affect how different factors, like convenience and service quality, relate to one another when it comes to the use of AI (Siau & Wang, 2018; Ferrario, Loi, & &Vigan` o, 2019).

2.2.4 Grounding

It is important to communicate with AI agents continuously since this produces data that can improve system performance. Users and the system share cognitive knowledge through their mutually beneficial interaction; "grounding" is essential to building mutual understanding (Jeon, 2024). Although collaborative grounding with AI systems presents challenges, human communication achieves this inherently (Kontogiorgos et al., 2021). Through clear verbal and nonverbal cues that indicate understanding of earlier conversational elements, grounding indicates mutual understanding in conversation (Richardson & Dale, 2005). Grounding verifies that the audience has comprehended the speaker's earlier remarks; it doesn't present any new information. True linguistic grounding is still difficult to achieve, even if robots can display non-linguistic grounding signals (Jeon, 2024).

Users should approach machine interactions differently and emphasising that the rules governing interpersonal trust might not apply to human–machine trust (Clark et al., 2019; Madhavan & Wiegmann, 2007). Users perceive interactions with agents as predominantly transactional and perceive computer talks as utilitarian, differentiating between social and transactional functions. When making trust judgements about machines, they place a higher value on factors like security and performance and question the need for humans to build relationships with machines (Clark et al., 2019).

Grounding is the crucial process of creating mutual understanding when convergence serves as the primary interface between humans and machine. An important factor in this process is the communication medium (Clark & Brennan, 1991; Kontogiorgos et al., 2021). According to Kontogiorgos et al. (2021), face-to-face interaction is the richest form of human communication, but working together to jointly build a common ground with robots could be difficult, just as it is for human speakers (Cahn & Brennan, 1999; Hildreth et al., 1998). Thus, consumers build common ground with AI-Chatbots based on security and service quality, improve their experience.

2.2.5 Customer Experience

Creating and improving the customer journey referred to as the customer experience with the company is the goal of modern marketing initiatives (Lemon & Verhoef, 2016). Customers' internal and subjective reactions to any direct or indirect interaction with the business are now referred to the customer experience (Schwager &

Meyer, 2007), while it is the culmination of thoughts, feelings, and attitudes formed over a coherent series of interactions with people, things, and the environment (Rizomyliotis et al., 2022). The notion of customer experience is proposed to encompass a multifaceted (i.e., affective, cognitive, perceptual, interpersonal, and behavioural) customer reaction to a commercial offer or correspondence (Jaakkola, Helkkula, & Aarikka-Stenroos, 2015; Rizomyliotis et al., 2022).

In AI-Chatbot service, the emotional aspect of the user experience is affected when emoticons are used (Bleier et al., 2019; Brakus et al., 2009; Lemon & Verhoef, 2016). A crucial precondition of the customer experience is the recognition of the customers' emotions (McLean et al., 2018; Edvardsson, 2005).

Businesses started to highlight experiences as a major offering to clients in the later phases of Pine and Gilmore's "experience economy," much like they do with goods, commodities, and services. However, the study which expanded on Pine and Gilmore's framework was the first to conduct a thorough investigation and analysis of customer experience in marketing (Knidiri, 2021). Using five strategic experiential modules (SEMs), "sense," "feel," "think," "act," and "relate", the researcher distinguished between traditional marketing and experiential marketing. According to his theory, things that convey relational, emotional, sensory, behavioural, and cognitive values cause customers to interact with them and create experiences (Verhoef et al., 2009).

In analysing the customer experience, the study considered both intrinsic and extrinsic customer values and evaluated AI-Chatbots on responsiveness and usability (Chen et al., 2021).

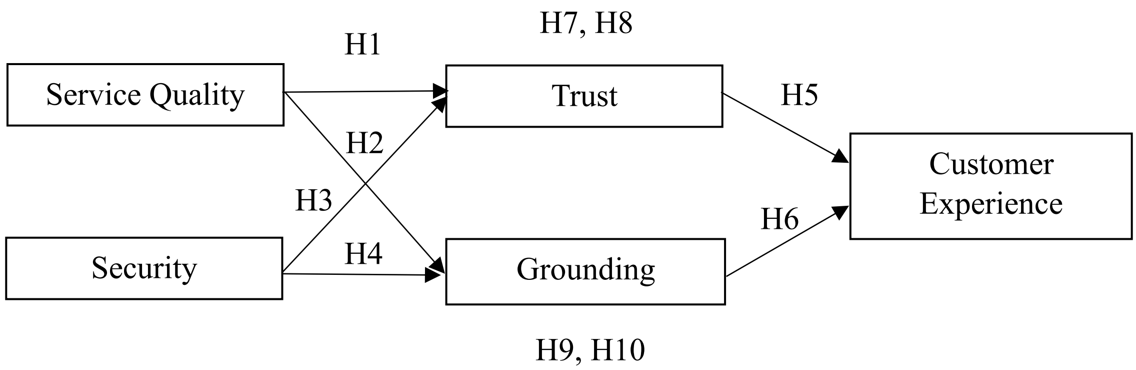
Separating extrinsic from intrinsic values, the research investigates how AI-Chatbots affect the online customer experience. When AI-

Chatbots are used well, businesses can provide a personalized experience that makes users feel valued and at ease while also enhancing extrinsic benefits like convenience, efficiency, and time savings (Weurlander, 2023).

When interacting online, where the AI-Chatbot experience should be smooth and engaging, intrinsic values like a sense of accomplishment, independence, and enjoyment are essential (Weurlander, 2023). Customers experience greater accomplishment and satisfaction when interacting with responsive AI-Chatbots, which enhances both intrinsic and extrinsic benefits. AI-Chatbots are crucial in customer interactions because of their reliability and usability, which improve customer satisfaction and the online experience (Chen et al., 2021).

2.3 Proposed Framework

Figure 2.1: Research Proposed Framework



Source: Developed for the research.

This study's conceptual framework illustrates how customer experience is impacted by internal organismic responses (AI-Chatbot user trust and grounding) that are influenced by external stimuli (five dimensions of AI-Chatbot service quality and security). Due to users' perceptions of the AI-Chatbot as trustworthy, knowledgeable, and transparent, high AI-Chatbot service quality and security (S) increases AI-Chatbot user trust (O) (Rafiq et al., 2022).

Since users find AI-Chatbot interactions to be simple, personalised, and emotionally fulfilling, high AI-Chatbot service quality (S) also plays a positive role in the AI-Chatbot user trust and grounding (O). The growth of trust is influenced by sentiments and emotions, since unfavorable feelings can make people distrustful of other people (Hoff & Bashir, 2015). In this research setting, the "organism" can be the process by which customers build trust in the text-based chatbot. Positive trust and grounding further stimulate the creation of a positive AI-Chatbot user experience (R) among users.

Higher levels of customer experience (R) are boosted by the combined effects of positive AI-Chatbot user trust (O) and grounding (O). On the other hand, AI-Chatbot service quality (S) is subpar. It will result in decreased customer experience (R), a lower AI-Chatbot user trust (O) and grounding (O).

Past research has shown that there is a relationship between e-brand loyalty and AI-Chatbot service quality; therefore, our study framework can serve as a theoretical foundation and guide for doing so (Ho & Chow, 2023; Ittefaq et al., 2024).

2.4 Hypotheses Development

2.4.1 The effect of service quality on customers' trust

When discussing AI-Chatbots, service quality takes into account a number of factors, including tangibles, reliability, responsiveness, assurance, and empathy. Building trust with customers is achieved through consistent and dependable AI-Chatbot interactions (Hsu & Lin, 2023). High-quality service can be reliably provided by AI-Chatbots. It's possible that human employees experience fatigue-related errors or feelings of exhaustion, but not with them (Ruan & Mezei, 2022). Thus, if AI-Chatbot provide high service quality to customers consistently, their trust is strengthened. Customers are assured of consistently receiving the same caliber of service. According to earlier research, customers' perceptions of brands are influenced by the technical and functional quality of services (Chiou & Droge, 2006; Eisingerich & Bell, 2008). When considering a service provider, customers may form an initial level of trust based on the technology they use and how they use it, especially if there is no other information available (Ameen et al., 2021).

H1: Service quality has positive effect on trust.

2.4.2 The effect of service quality on grounding

Another aspect of perceived service quality is responsiveness, which encompasses staff members' readiness to provide a service that includes timely responses, prompt answers, and prompt service (Parasuraman et al., 1985). According to Meyer-Waarden et al. (2020), a provider's perceived quality of service will rise if it becomes more responsive. According to the least collaborative effort principle, people should try to ground with the least amount of shared effort possible (Clark & Brennan, 1991). The medium is more conducive to grounding when the AI-Chatbot is responsive and high service quality because can lower the total effort required. High service quality of AI-Chatbot, customers tend to ground it. Thus, this research hypothesis that customer grounding rise when it can provide the required service responsiveness. There is a gap when the service provider fails to live up to the customers' expectations. It also results from the two parties' insufficient communication and lack of comprehension of one another (Duy, 2021). Therefore, this study hypothesizes that when an AI-Chatbot provides customers with expected high service quality, the sense of grounding will rise.

H2: Service quality has positive effect on grounding.

2.4.3 The effect of security on trust

When interacting with AI-Chatbots, users need to feel confident that their personal information is safe and secure. For companies and organisations that depend on AI-Chatbots for customer service and support, a security breach could erode this trust and have dire consequences (Yang et al., 2023). Numerous experts on privacy contend that trust is a crucial factor in privacy risks (Raab, 1998). Data breaches, reputational harm, decreased consumer trust, and severe fines and penalties can all be brought on by a weak AI security and privacy framework (Li, 2023). When an AI-Chatbot consistently offers excellent assistance, it fosters trust in interactions with users. Relying on the AI-Chatbot to meet their needs gives customers confidence. The way that clients view the security and privacy of their data when interacting with the AI-Chatbot is another factor that influences trust (Shahzad et al., 2024). Thus, this research hypothesis that security should be a significant element positively influence trust.

H3: Security has positive effect on trust.

2.4.4 The effect of security on grounding

Although using these technologies well unquestionably increases user engagement and simplifies communication processes (Følstad et al., 2018; Zamora, 2017), the goal of creating conversational text-based AI-Chatbots must be carefully examined. Significant privacy and security concerns are raised by AI-Chatbots' data collection capabilities, which are advantageous for customisation and improving user experience (Adam et al., 2020; Gumusel et al., 2024). Maintaining strong privacy and security protocols while acknowledging the vital necessity of data collection to improve user interactions is crucial. It is important to take a careful and responsible approach to AI-Chatbot development, as evidenced by the change in focus from talking about the benefits of AI-Chatbots to addressing privacy concerns (Gumusel et al., 2024). By utilizing AI-Chatbot can mutual communication with customers to simplifies communication processes, but this depends on the security of AI-Chatbot. This research hypothesize that security should be a significant element positively influence grounding.

H4: Security has positive effect on grounding.

2.4.5 The effect of trust on customer experience

Competence, generosity, and honesty are the foundations of trust in an intelligent recommender system. By allaying doubts about their skills and motivations, this trust increases the perceived utility of recommendation agents (Bleier & Eisenbeiss, 2015). Believing that the trustee can fulfil the expectations of the trustor is the foundation of competence. Consumers look to AI applications to provide them with helpful, individualized, and reliable recommendations. The idea that the trustee (AI system) will prioritise the interests of the trustor, or consumer, over its own, is reflected in the concept of benevolence in this context. The trust that the trustee will be truthful and honour its commitment is the final component of integrity (Venkatesh et al., 2011). According to Siau and Wang (2018), AI needs trust to be embraced and developed. The study demonstrates that without trust, people are hesitant to use a brand's AI services, which makes adoption crucial. Ling et al. (2010) presented trust as an independent factor influencing customer experience. It can be seen from the statement that when customers build trust in AI services, they are more likely to accept and utilize AI services for their experience. This research hypothesis that trust should be a significant element positively influence customer experience.

H5: Trust has positive effect on customer experience.

2.4.6 The effect of grounding on customer experience

Communication between humans and AI systems is essentially a two-way process whereby the user provides feedback to the AI system and the AI system uses system outputs to communicate its understanding of the user. Unfortunately, there are two potential points of failure in this communication process: either the AI systems or the users misinterpret what the AI is trying to tell them (Riedl, 2019). Therefore, when the AI-Chatbot does not provide mutual communication with customers, customers may not interact and ground with the AI-Chatbot. It will decrease customer experience in using AI-Chatbot. This research hypothesis that grounding should be a significant element positively influence customer experience.

H6: Grounding has positive effect on customer experience.

2.4.7 Mediating effect of trust between service quality and customer experience

The association between trust and customer experience has been examined in earlier research, either by looking at trust as a mediator (e.g. Martin, Mortimer, & Andrews, 2015; Rose et al., 2012). When using a technology-enabled service, where they trust the brand, the process, and the technology customers begin to have positive expectations and feel more at ease (Alsajjan & Dennis, 2006). Thus, the influence that service quality has on the customer experience is amplified in the presence of trust. Additionally, prior research suggests that trust acts as a mediator in the connection between loyalty and service excellence (Ameen et al., 2021). A service's willingness to be trusted increases with consumer knowledge of it (Eisingerich & Bell, 2008). Therefore, if customers have trust in the technology, they are likely to have a more positive experience with it. Ramadan et al. (2024) seems to have stressed that a positive feedback loop resulting in a positive customer experience is created by brand trust. Brand confidence and trust can be increased when AI-Chatbots reliably provide accurate and pertinent information. Positive user experiences increase a customer's likelihood of developing an emotional bond with the brand and earning their trust (Van den Broeck et al., 2019). Consequently, this research hypothesis that trust mediates on service quality and customer experience.

H7: Trust mediates the relationship between service quality and customer experience.

2.4.8 Mediating effect of trust between security and customer experience

According to Agnihotri & Bhattacharya (2023), pointed out the detrimental effect on user engagement, while Marjerison et al. (2022) draw attention to security concerns in e-commerce AI-Chatbot data breaches. Making AI-Chatbot speech more human-like with better AI-Chatbot design techniques (Hasal et al., 2021). As a result, social media AI-Chatbots will become more trustworthy, and be more influencing people's opinions (Feine et al., 2020). Users' perception of how secure AI-Chatbots are influences their trust and affects the entire experience. Positive customer experiences are diminished when trust is not reinforced by robust security measures, even in AI-Chatbots with exceptional features and human-like conversational abilities. While the overall user experiences, confidence, and interactions are improved if it's perceived as secured. This research hypothesis that trust mediates security and customer experience.

H8: Trust mediates the relationship between security and customer experience.

2.4.9 Mediating effect of grounding between service quality and customer experience

By confirming active listening and promoting intimacy and understanding, grounding link together conversational turns. By fostering shared ideas and emotions, understanding human relationships resolves conflicts and strengthens emotional bonds (Weger et al., 2014). Customer' perceptions of salespeople is greatly influenced by these attributions, which in turn affects the establishment of trust and their propensity for repeat business. For relationships to develop, it is essential to identify and establish shared knowledge during conversations (Reis et al., 2017). When there is a transparent communication of information and understanding between the customer and the AI-Chatbot, grounding takes place. By creating a feeling of understanding and value, grounding improves the customer experiences. The interaction will seem more pleasant, intimate, and emotionally satisfying to customers if they sense that the AI-Chatbot is actively listening to them and meaningfully interacting with them. Customers may find an interaction with an AI-Chatbot unsatisfactory even if its functional service quality is strong and lacks grounding. This research hypothesis that grounding acts as a mediator between the quality of services provided by the AI-Chatbot and the customer experience.

H9: Grounding mediates the relationship between service quality and customer experience.

2.4.10 Mediating effect of grounding between security and customer experience

Data-sharing procedures in AI-Chatbots highlights possible security risks (Sannon et al., 2020; Gumusel et al., 2024). Grounding is important for relationship development, contribution recognition, and creating shared knowledge (Clark & Brennan, 1991; Reis et al., 2017). Customers may face potential security risks when using AI-Chatbot, reducing recognition of contributions to customers, results in less customer grounding of the AI-Chatbot. Informed and reassured users about the AI-Chatbot's sharing and protection of their data may result effective grounding leading to have a better overall customer experience when they feel secured. Thus, this research hypothesis that grounding mediates the relationship between the service quality and security of AI-Chatbot and customer experience.

H10: Grounding mediates the relationship between security and customer experience.

2.5 Conclusion

After reviewing earlier research, this chapter covered underlying theory, literature review of variables and developed the research framework and hypotheses. In chapter three, the research methodology will be discussed.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter reviews the research design, sampling design, constructs measurement, measurement scales, data collection methods, and data analysis tool.

3.1 Research Design

It is possible to create a research design that offers a structure for data collection and analysis (Kronemann, 2022). Research design can be descriptive, exploratory, and causal research designs. This study is causal and collects and analyses data using quantitative approaches.

3.1.1 Causal Research

To determine the scope and character of cause-and-effect relationships, causal research also knowns as explanatory research. Causal research can evaluate the effects of changes on established norms. The goal of causal studies is to explain patterns of relationships between variables by analysing a situation or a particular issue. Through specific causal evidence that cause-and-effect relationships can be verified. Consecutive variation, temporal sequence, and nonspurious association are the three main elements of causal evidence. Priority of cause over effect is temporal sequence. Variation that occurs consistently between the two variables is concurrent variation. If a cause-and-effect covariate, it must be real and not the result of a third variable, according to the theory of nonspurious association. That is, neither the cause nor the effect should be related to any outside factor (Dudovskiy, 2012). This research is causal research as it intends to collect data to assess the factors affecting customers' experience in using AI-Chatbot.

3.1.2 Quantitative Research

There are two different types of methodological approaches: quantitative and qualitative (Kronemann, 2022). A methodology known as quantitative research employs statistical analysis and places a strong emphasis on quantification in the gathering and processing of data (Allen, 2017; Kronemann, 2022; Malhotra, 2004). Due to its focus on testing theories that have been developed through analysis of existing literature, a quantitative strategy is deductive in nature (Allen, 2017; Bell & Waters, 2014; Kronemann, 2022). This means that when a researcher gathers a large sample and performs statistical analysis of the data, a quantitative methodology is appropriate for the positivist perspective. Quantitative methods have been proven to be useful for measuring customer behaviour and for conducting customer surveys (Kronemann, 2022). According to Malhotra (2004), quantitative techniques are also helpful for analysing big datasets. This research use quantitative approach is appropriate as it intends to collect a sizable sample to assess the factors affecting customers' experience in using AI-Chatbot.

3.2 Sampling Design

This research chooses a sample to collect data before beginning data collection. The process of choosing items from a population of interest so that conclusions of target population can be drawn from the sample is known as sampling design (Kothari, 2004). By evaluating the sample, one could logically extrapolate the findings to the intended population.

3.2.1 Target Population

The entire set of elements for which survey data are to be gathered to draw conclusions is the target population (Lavrakas, 2008). In this study, the unit of analysis is the individual customer. A person who "purchases goods and services for personal use" is referred to as a "customer" (Kronemann, 2022). A customer's prior interaction with an AI application in an online context previously, such as a AI-Chatbot, virtual assistant, or recommendation agent serves as the selection criterion for the targeted unit of analysis. The requirement arises from the fact that the purpose of the research is to investigate how the AI-Chatbot will affect the customer experience. The target population of this research is customers who has experience with AI-Chatbot related products previously.

3.2.2 Sampling Frame

The sampling frame, or the list of units from which the sample was taken, is how the population is defined in practice. Ideally, every unit within the specified population should be included in the sampling frame (Forthofer & Hernandez, 2007). A perfect frame has no extraneous or irrelevant population elements listed, and each element in the population is listed separately only once (Baker et al., 2010). In this research, the targeted population is target on interaction with an AI application in an online context previously, like AI-Chatbot, virtual assistant, or recommendation agent. The current study does not have a sample frame for individual customers who use AI-Chatbot related products previously as the sample consists of a large number of individual customers.

3.2.3 Sampling Technique

There two sampling techniques can choose either probability sample or non-probability sample. This research chooses non-probability sample. Any technique for gathering survey data that doesn't make use of a complete probability sampling design is referred to as nonprobability sampling. Nonprobability samples are generally easier to collect and less expensive than probability samples because they do not have a sampling frame (Forster, 2001). Kronemann (2022) distinguished between two categories of non-probability sampling techniques: quota sampling and convenience sampling. Quota sampling aims to produce a sample that, in terms of relative proportions, represents the population across a number of categories, including gender, ethnicity, and income. Convenience sampling is a popular non-random population sample technique. Selection of study subjects based on convenience sampling occurs when participants are available to the researcher for various reasons (Stratton, 2023). This research decided to use convenience sampling to collect data from online customers.

3.2.4 Sample Size

Finding the ideal sample size which indicates the quantity of participants needed to complete the online questionnaire. Since sample size affects sampling error, sample size considerations are very important. The larger the sample size that is necessary, the less sampling error that the researcher is willing to accept (Kronemann, 2022). According to Roscoe (1975), a minimum of 10 times the number of variables should be included in the sample size when performing multivariate analytic research. Expanding on this idea, the author says that most studies will benefit from a sample size of 30 to 500. For "good" sampling, Kronemann (2022) recommend at least 300. Thus, the minimum sample size of this research is 300. The final sample size is 334 sample size.

3.3 Data Collection Methods

For statistical analysis to be performed, data collection is essential. Research employs a range of data collection methodologies, which can be categorized into two groups, both primary and secondary sources of information (Ajayi, 2023).

3.3.1 Primary Data

The first set of original, factual and real-time data that a researcher collects is called primary data. To find a solution to the current issue, primary data is gathered. It is a term used to describe information that was first created by the researcher (Mesly, 2015). The process of gathering primary data is complex than secondary data. Primary data sources include things like surveys, tests, observations, questionnaires, in-person interviews, and more (Ajayi, 2023). An online survey in the form of a self-completion questionnaire has been selected as the method of data collection for this research (Kronemann, 2022). This study collected primary data from customers who had previously used AI-Chatbot through a self-administered questionnaire.

3.3.1.1 Questionnaire

Given that respondents typically complete questionnaires and provide answers on their own, which is a common practice in the social sciences, a questionnaire has been chosen as the effective means of gathering data (Kronemann, 2022). compared to interviews, self-completion questionnaires have less risk of social desirability bias in respondents' answers because they are quicker and less expensive to administer. Additionally, because respondents can complete the questionnaire at any time and place of their choice, it is more convenient for respondents to respond to the questionnaire than the interview (Kronemann, 2022; Saunders et al., 2019). Since closed questions are simpler to respond to and lower the possibility of "respondent fatigue," it is advised that a questionnaire primarily consist of closed questions (Kronemann, 2022). Since closed questions facilitate statistical analysis, hypothesis testing, relationship analysis between research model constructs, and research question answering, it is also used in previous studies, they were chosen to study how artificial intelligence affects customer adoption of artificial intelligence devices e.g. (Kronemann, 2022; Moriuchi, 2019).

3.4 Constructs Measurement

3.4.1 Source of the Questions

Table 3.1: Measurement Items

Construct	**Item**	**Original Item**	**Source**	**Modified Item**
Service Quality (SQ)	SQ1	Flybot has attractive Messenger colours.	Meyer-Waarden et al., 2020	AI-Chatbot has attractive Messenger colours.
	SQ2	Flybot has attractive website colours.		AI-Chatbot has attractive website colours.
	SQ3	Flybot has an attractive appearance.		AI-Chatbot has an attractive appearance.
	SQ4	Flybot is useful.		AI-Chatbot is useful.
	SQ5	Flybot is reliable.		AI-Chatbot is reliable.
	SQ6	Flybot gives useful information.		AI-Chatbot gives useful information.
	SQ7	Flybot gives real information.		AI-Chatbot gives real information.
	SQ8	Flybot responds quickly.		AI-Chatbot responds quickly.

	SQ9	Flybot responds immediately.		AI-Chatbot responds immediately.
	SQ10	Flybot is credible.		AI-Chatbot is credible.
	SQ11	Flybot is impartial.		AI-Chatbot is impartial.
	SQ12	Flybot is well-informed.		AI-Chatbot is well informed.
	SQ13	Flybot is qualified.		AI-Chatbot is qualified.
	SQ14	Flybot is an expert.		AI-Chatbot is an expert.
	SQ15	Flybot is sympathetic.		AI-Chatbot is sympathetic.
	SQ16	Flybot is honest.		AI-Chatbot is honest.
	SQ17	Flybot is attentive.		AI-Chatbot is attentive.
Security (SE)	SE1	I feel safe in my interaction with this AI bot.	Hsu & Lin, 2023	I feel safe in my interaction when using AI-Chatbot.
	SE2	I feel my privacy is protected by this AI bot.		I feel my privacy is protected by AI-Chatbot.
	SE3	I trust this AI bot will not misuse my personal information.		I trust that AI-Chatbot will not misuse my personal information.

	SE4	I feel I can trust this AI bot.		I feel I can trust AI-Chatbot.
	SE5	This AI bot instills confidence in me.		AI-Chatbot instills confidence in me.
Trust (TR)	TR1	Flybot engages me.	Meyer-Waarden et al., 2020	AI-Chatbot engages me.
	TR2	Flybot puts my interests first.		AI-Chatbot puts my interests first.
	TR3	Flybot keeps its promises.		AI-Chatbot keeps its promises.
	TR4	Flybot gives perfect service quality.		AI-Chatbot gives perfect service quality.
Grounding (GO)	GO1	This AI agent provided feedback on having accepted my input.	Jeon, 2024	AI-Chatbot provided feedback on having accepted my input.
	GO2	I felt that this AI agent understood what I had to say.		I felt that AI-Chatbot understood what I had to say.
Customer Experience (CE)	CE1	I am satisfied with the service agent.	Chung et al., 2020	I am satisfied with the AI-Chatbot.
	CE2	I am content with the service agent.		I am content with the AI-Chatbot.

	CE3	The service agent did a good job.		The AI-Chatbot did a good job.
	CE4	The service agent did what I expected.		The AI-Chatbot did what I expected.
	CE5	I am happy with the service agent.		I am happy with the AI-Chatbot.
	CE6	I was satisfied with the experience of talking with the service agent.		I was satisfied with the experience of communicating with the AI-Chatbot.

Source: Developed for the research.

3.4.2 Measurement Scales

In the processes of gathering, analysing, and presenting data, measurement scale is crucial. The statistical instruments used in data collection and analysis vary depending on the type of data (Mishra et al., 2018). Nominal scale, ordinal scale, interval scale, and ratio scale are the four types of scales (Anjana, 2021). This research utilises two measurement scales in statistics which are nominal scale and interval scale.

3.4.2.1 Nominal Scale

A scale used to classify variables into distinct categories is called a nominal scale, also knowns as categorical variable scale. Since the numbers are intended to categorize and identify individuals, things, or events, they have no numerical worth or significance. The percentage and frequency distribution are the statistical analyses on a nominal scale. A bar chart or a pie chart can be used for a graphic analysis. With this scale, the mode is the only way to quantify central tendency. To find this scale's central tendency, utilise the arithmetic mean, median, and mode. Calculations can be used to determine dispersion metrics like range and standard deviation (Anjana, 2021). Nominal scales are used in current research to analyse categorical variables are gender, age, ethnicity, level of study, monthly income and the general questions.

3.4.2.2 Interval Scale

A quantitative measure where the precise difference between categories and their order are known is called an interval scale. Consequently, it measures variables with equal intervals, labels, and ordering. On an interval scale, the zero point, or point of beginning, is not a "true zero" or "absolute zero," but rather is determined arbitrarily. Therefore, the characteristic being measured is not completely absent when the value is zero. To find this scale's central tendency, utilise the arithmetic mean, median, and mode. Calculations can be used to determine dispersion metrics like range and standard deviation (Anjana, 2021). The degree to which the respondent agrees or disagrees with the mentioned variable has been indicated in this research using a 5-point Likert scale.

3.5 Proposed Data Analysis Tool

Data analysis in research is crucial to increase the effectiveness of the study's findings (Alem, 2020). For partial least squares structural equation modelling (PLS-SEM), one of the well-known software programs is called SmartPLS. SmartPLS is developed by Ringle, Wende & Will in 2005. Due to its easy-to-use interface, advanced reporting features, and free access to academics and researchers, the application has gained popularity since its launch in 2005 (Wong, 2013). This research utilities SmartPLS to get results of reliability analysis, and partial least squares structural equation modelling (PLS-SEM).

3.5.1 Descriptive Analysis

The first step of analysis that is used to characterise and condense data is called descriptive statistics. This section of the statistic was strengthened by the abundance of data and the highly effective computing techniques (Sarmento & Costa, 2017). By finding data patterns to respond to questions about who, what, where, when, and to what extent, quantitative descriptive analysis characterises the world or a phenomenon. Data implication is descriptive analysis (Loeb et al., 2017). The data collected from the demographic section and general questions were used for descriptive analysis and will use frequency and percentage of frequency to describe the trends of it.

3.5.2 Reliability Analysis

Draw the conclusions that fairly represent the opinions of respondents, reliability analysis guarantees that the data is objective and consistent, satisfying the standards of high-quality research (Zikmund, 2003). The consistency and stability of the instruments with the concepts to be measured must be ascertained through a reliability test (Sekaran, 2003). Examining a construct's internal consistency and dependability is the goal of composite reliability assessment. Nevertheless, Cronbach's alpha assumes that every item has an equal outer loading on the construct and is equally reliable

(Hair et al., 2014). By utilising SmartPLS, this research utilises composite reliability to rank the items based on their individual reliability as the limitation of Cronbach's alpha. Higher estimates of true reliability may result from composite reliability as opposed to Cronbach's alpha (Garson, 2016). In the range of 0 to 1, there are composite reliability values. A greater level of reliability is associated with a higher composite reliability (Haji-Othman & Yusuff, 2022). Hair et al. (2014) indicated that composite reliability values in the range of 0.60 to 0.70 are considered acceptable. Insufficient internal consistency reliability is indicated by composite reliability values below 0.60.

3.5.3 Pilot Test

Pilot study is crucial as it is carried out to find any possible flaws or trouble spots in the protocol and research tools before the full study is implemented (Hassan et al., 2006). When evaluating the quality and appropriateness of an instrument, validity and reliability are crucial. Validity guarantees that the instrument measures what it is supposed to. Before applying reliability to real samples, small-scale testing refers to a sample that is nearly as homogeneous as the actual sample is necessary to ensure consistent results. The pilot test's sample size is limited to five to thirty individuals (Sundram & Romli, 2023).

In the pilot test, the study used 30 respondents to test the reliability and validity. Table 3.2 presents the composite reliability (CR) for every build varies from the highest construct CR value, CE, at 0.950, to 0.877 for TR. By examining the composite reliability rho_c, all the construct measures are above the 0.70 threshold. All three reflective constructs have excellent levels of internal consistency dependability, as seen by their rho_a values of 0.940 (CE), 0.794

(GO), 0.923 (SE), and 0.813 (TR). Consequently, each construct in the study was above the recommended range of acceptable values of 0.60 to 0.70. The AVE ranged from 0.705 to 0.829 higher than the threshold of 0.50. As a result, the constructs in the model are proven to be valid and reliable.

Table 3.2: Reliability Analysis

Variables	**Cronbach's alpha (CA)**	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Customer Experience (CE)	0.937	0.940	0.950	0.761
Grounding (GO)	0.793	0.794	0.906	0.829
Security (SE)	0.921	0.923	0.940	0.760
Trust (TR)	0.792	0.813	0.877	0.705

Source: Developed for the research.

3.5.4 Partial Least Squares Structural Equation Modelling (PLS-SEM)

PLS is a soft modeling technique for SEM that does not make any assumptions about the data distribution (Vinzi et al., 2010). Partial Least Squares Structural Equation Modelling (PLS-SEM) is useful than CB-SEM as the sample size is small, the available theory for applications is limited, the accuracy of predictions is crucial, it is not possible to guarantee accurate model specifications (Bacon, 1999; Hwang et al., 2010; Wong, 2010). PLS is useful for structural equation modeling in practical research projects when there are few participants and a skewed data distribution (Wong, 2011).

To test measurement model, in PLS-SEM got to test convergent validity and discriminant validity. An item's positive correlation with other items belonging to the same construct is known as convergent validity. Convergence indicates that a large percentage of variance is shared by the items in each construct. Convergent validity is examined in this study by combining the average variance extracted (AVE) with the item's outer loadings. AVE is calculated by averaging the squared loadings of the elements associated with a specific construct. If a construct has an AVE of 0.50 or above, it is thought to account for more than half of the variation of its elements. A minimum of 0.5 is allowed. There are typically still more errors in the items if the AVE is less than 0.50. If the outer loading is less than 0.40, remove the item. If outer loading is greater than 0.40 but less than 0.70, assess how eliminating the item might affect AVE and composite reliability. If deleting the item causes the composite dependability and AVE to rise beyond the threshold, it should be done. However, if eliminating the item does not increase the AVE and composite dependability above the cutoff, maintain it. If the outside loading is more than 0.70, the item should be retained (Hair et al., 2014).

Through simulation studies, Henseler et al. (2015) showed that the heterotrait-monotrait (HTMT) ratio they developed is a more effective way to identify lack of discriminant validity. By dividing the average of monotrait-heteromethod correlations (within the same construct) by the geometric mean of heterotrait-heteromethod correlations (across constructs measuring different phenomena), the HTMT ratio is calculated. When two monotrait-heteromethod submatrices exist, as when two constructs are present, the geometric mean is employed. Below 1.0 is the best HTMT ratio (Garson, 2016). For the examination of discriminant validity, rigorous criteria need HTMT 0.85, while a more flexible HTMT criterion (HTMT.90 or HTMT inference, depending on sample size) can be appropriate (Henseler et al., 2015).

The Fornell-Larcker criterion and factor loadings are further techniques for testing discriminant analysis. The Fonrell-Lacrker criterion compares the square root of the AVE to the correlation of latent constructs. A latent construct should be better at describing the variation of its own signal than it should be at explaining the variance of other latent constructs. Therefore, the square root of each construct's AVE should be greater than the correlations with other latent constructs (Hair et al., 2014). The threshold value of 0.708, which denotes adequate levels of indicator reliability (SmartPLS, n.d.).

To test the structural model, in PLS-SEM got to test collinearity, path coefficient, R^2, and f^2. In multiple regression models, the classical definition of collinearity is the predictor-predictor phenomenon (Kock, 2015). Regression model predictor variables become less significant statistically and less able to predict the dependent variable independently when they exhibit correlation or sharing some of the same variance (Enders, 2019). According to Hair et al. (2021), variance inflation factor (VIF) is the standard statistic used to evaluate indicator collinearity. The degree of collinearity increases with higher VIF levels. Collinearity issues are indicated by VIF ≥ 5. Collinearity problems are not serious if VIF is between 3 and 5. If VIF is less than 3, collinearity is not a concern. A high variance inflation factor (VIF) or a significant increase in the p-value of one variable when another is added to the model are signs of high correlation between two predictor variables, which raises concerns about collinearity in regression (Enders, 2019).

Standardised path coefficients refer to path weights range from -1 to +1. The strongest and weakest paths are reflected by weights closest to absolute 1 and closest to 0 respectively (Garson, 2016). The traditional 0.05 threshold for the p value (Leo & Sardanelli, 2020). A p-value greater than 0.05 will be found if the ratio's 95% confidence interval contains the number 1. On the other hand, the p-value is strictly less than 0.05 if the value 1 is absent from the 95% confidence interval. The standard deviation (σ) quantifies the range of observations around the mean. Data that is close to the mean is indicated by σ around zero, tight clustering is shown by low σ, and broader dispersion is indicated by high σ (Tan & Tan, 2010).

The correlations found are significant if the t-value in bootstrapping is greater than 1.96. The t-value of þ/-1.96 is the maximum value that should be produced by a 5% chance (Ghorbani et al., 2019). The overall effect size measure for the structural model, similar to regression, is the R-square, also known as the coefficient of determination (Garson, 2016). Results above the cutoffs of 0.67, 0.33, and 0.19 are characterised as "substantial," "moderate," and "weak," respectively (Chin, 1998; Höck & Ringle, 2010). An alternative term for the R^2 change effect is the f^2 effect size measure. The amount of unexplained variance that R^2 change accounts for is expressed by the f^2 equation (Hair et al., 2014). The f^2 effect sizes of .02,.15, and.35, respectively, correspond to "small," "medium," and "high" effects (Cohen, 1988).

3.6 Conclusion

Research methodology offers an organised framework for carrying out studies in accordance with predetermined standards to conduct consistent results. This chapter has covered research design, sampling design, data collection methods, constructs measurement, measurement scales and data analysis tool.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

Research instrument, construct measurement, data processing, data analysis techniques, sample design, data collection method, and research design were all covered in the previous chapter. The outcomes of the various analysis techniques that were conducted using the statistical analysis program Smart PLS 4 are described in this chapter.

4.1 Descriptive Analysis

4.1.1 General Questions

4.1.1.1 Respondents who used AI-Chatbot related products

Table 4.1 presents the total respondents has been collected is 385 respondents. Among the 385 respondents, 355 respondents who used AI-Chatbot related products, accounting for 92.2% of respondents, while 30 respondents who did not used AI-Chatbot related products, accounting for 7.8% of respondents. Respondents who have used AI-Chatbot related products make up the study's target demographic. For this study, 355 respondents were chosen. After data cleaning, only 334 respondents remain, as there are outliers and straight-lining responses. These 334 respondents are valid responses.

Table 4.1: Respondents who used AI-Chatbot Related Products

Respondents who used AI-Chatbot related products	Frequency	Per cent
Yes	355	92.2
No	30	7.8
Total	385	100.0

Source: Developed for the research.

4.1.1.2 Types of AI-Chatbot Used

Table 4.2 indicates that 55% of the total, used ChatGPT, while 18.2% respondents used Google Gemini. Total respondents who used Microsoft Copilot, Perplexity AI, Claude are 14.2%, 10.2%, 0.5% respectively. In contrast, only 0.2% of the total used AI Chat, Phind, Dify, Coze, Qwen, Quilbot, Character ai, Talkie, Poe, DeepseekAI, and Apple Siri.

Table 4.2: Types of AI-Chatbot Used

Types of AI-Chatbot used	Frequency	Per cent
ChatGPT	329	55.0
Google Gemini	109	18.2
Microsoft Copilot	85	14.2
Perplexity AI	61	10.2
AI Chat	1	0.2
Claude	3	0.5
Phind	1	0.2
Dify	1	0.2
Coze	1	0.2
Qwen	1	0.2
Quilbot	1	0.2
Character ai	1	0.2
Talkie	1	0.2

Poe	1	0.2
DeepseekAI	1	0.2
Apple Siri	1	0.2
Total	598	100

Source: Developed for the research.

4.1.1.3 Reason to Use AI-Chatbot

Table 4.3 indicates that 29.4% of the total respondents choose fast response and 24/7 customer service as their reason, while 26.7% respondents choose to provide easy-to-use self-service choices as their reason. Total respondents who choose to provide personalized response and choose support for multiple languages as their reason are 26% and 18% respectively.

Table 4.3: Reason to Use AI-Chatbot

Reason to Use AI-Chatbot	Frequency	Per cent
Fast response and 24/7 customer service	250	29.4
Provide personalized response	221	26.0
Provide easy-to-use self-service choices	227	26.7
Support for multiple languages	153	18.0
Total	851	100

Source: Developed for the research.

4.1.2 Respondent Demographic Profile

4.1.2.1 Gender

Table 4.4 presents the demographic profile of respondents. Among the 334 valid responses, 243 are from female respondents, accounting for 73% of the total, while 91 are from male respondents, representing 27%.

Table 4.4: Gender

Gender	**Frequency**	**Per cent**
Male	91	27
Female	243	73
Total	334	100

Source: Developed for the research.

4.1.2.2 Age

Table 4.5 indicates that 298 respondents, or 89.2% of the total, belong to the 18-25 years old, while 22 respondents, or 6.6% of the total, belong to the 26-35 years old. Respondents 36-45 years old and below 18 years old are 7 and 6 respondents respectively, accounting for 2.1% and 1.8% of the total number of respondents. In contrast, only 1 respondent, representing 0.3%, fall within the 46-55 years old and no respondents are above 55 years old.

Table 4.5: Age

Age	**Frequency**	**Per cent**
Below 18 years old	6	1.8
18 - 25 years old	298	89.2
26 - 35 years old	22	6.6
36 - 45 years old	7	2.1
46 - 55 years old	1	0.3
Above 55 years old	0	0
Total	334	100

Source: Developed for the research.

4.1.2.3 Ethnicity

Table 4.6 shows that most respondents are Chinese, accounting for 312 respondents or 93.4% of the total. This is followed by 12 Indian, 8 Malay, 1 Kadazan and 1 Korea.

Table 4.6: Ethnicity

Ethnicity	Frequency	Per cent
Chinese	312	93.4
Malay	8	2.4
India	12	3.6
Kadazan	1	0.3
Korea	1	0.3
Total	334	100

Source: Developed for the research.

4.1.2.4 Level of Study

Table 4.7 presents 275 respondents (82.3%) completed bachelor's degree, while 26 respondents (7.8%) possess UEC /STPM /A-Level /Foundation. This is followed by 17 respondents (5.1%) who completed master's degree, 15 respondents (4.5%) who completed Diploma, and 1 respondent who completed Doctorate Degree.

Table 4.7: Level of Study

Level of Study	Frequency	Per cent
UEC /STPM /A-Level /Foundation	26	7.8
Diploma	15	4.5
Bachelor's Degree	275	82.3
Master's Degree	17	5.1

Doctorate Degree	1	0.3
Total	334	100

Source: Developed for the research.

4.1.2.5 Monthly Income

Table 4.8 outlines the majority, 152 respondents (46%), receive an income of below RM500 per month. This followed by 80 respondents (24%) in the RM500-RM1000 range and 49 respondents (15%) in the RM1001-RM2000 range. The income of respondents belongs to above RM4000 and RM2001-RM3000 range are 22 and 21 respectively, accounting for 7% and 6% respectively. On the other hand, 10 respondents who receive RM3001-RM4000 per month.

Table 4.8: Monthly Income

Monthly Income	Frequency	Per cent
Below RM500	152	46
RM500 - RM1000	80	24
RM1001 - RM2000	49	15
RM2001 - RM3000	21	6
RM3001 - RM4000	10	3
Above RM4000	22	7
Total	334	100

Source: Developed for the research.

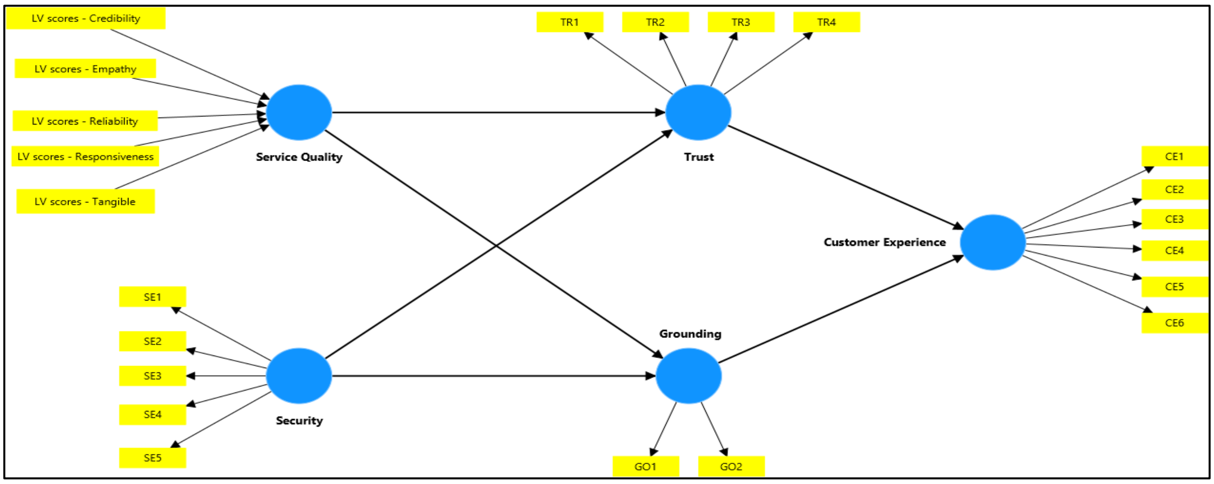
4.2 Confirmatory Factor Analysis

According to Costa & Sarmento (2019), CFA is a method that "tries to verify whether the quantity of factors (or constructs) and the loadings of observed (indicator) variables on them match what is anticipated based on theory." Therefore, it is essential to assess the validity and reliability of the scale to arrive at the confirmation and to correctly interpret how the constructs are represented by the observed variables. SmartPLS 4 software was used for this resesrch.

4.2.1 Inner and Outer Model Analysis Development

The outer model includes 22 items in total which are Service Quality had 5 items, Security had 5 items, Trust had 4 items, Grounding had 2 items, and Customer Experience had 6 items.

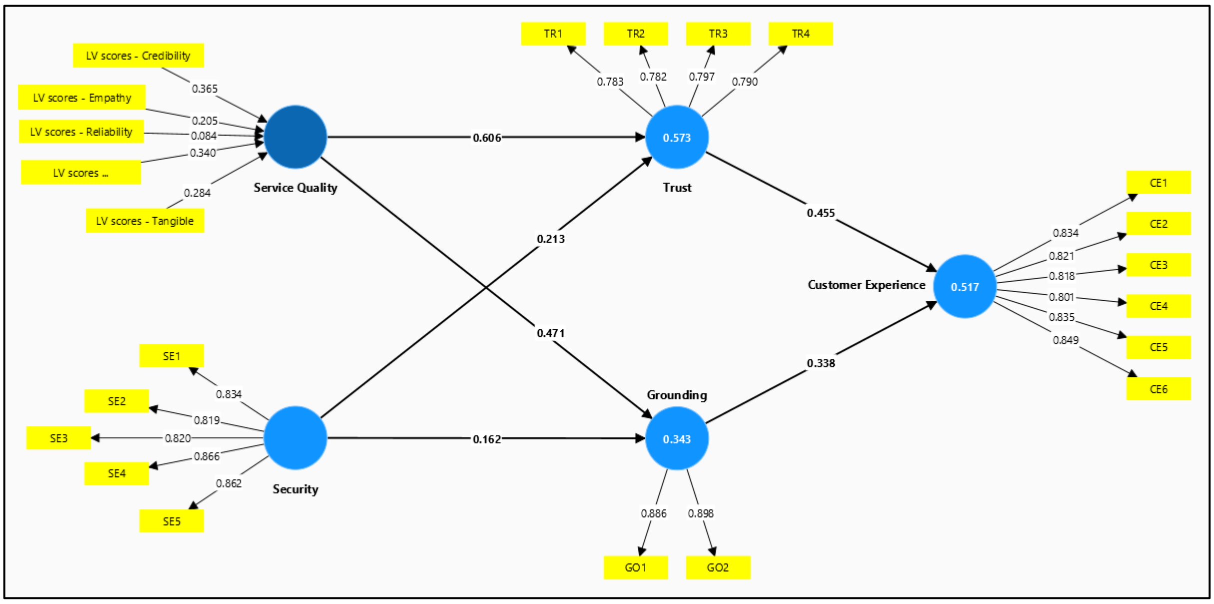
Figure 4.1: Development Model with Inner and Outer Paths



Source: Developed for the research.

4.2.2 Inner and Outer Model Analysis

Figure 4.2: Inner and Outer Model Analysis



Source: Developed for the research.

Figure 4.2 indicates all the items above the threshold of 0.7. All the items are acceptable. All the path coefficient values are positive. All the independent variables which are service quality, security, trust, grounding have positive impacts on customer experience in using AI-Chatbot.

4.3 Scale Measurement

4.3.1 Reliability Analysis

Table 4.9 presents the results of the internal consistency reliability analysis. The analysis being done is called Composite Reliability (CR). Hair et al. (2014) indicated that composite reliability values in the range of 0.60 to 0.70 are considered acceptable. High CR, High reliability. The analysis demonstrating the CR for every build varies from the highest construct CR value, CE, at 0.928, to 0.868 for TR. By examining the composite reliability rho_c, all the construct measures are above the 0.70 threshold. All three reflective constructs have excellent levels of internal consistency dependability, as seen by their rho_a values of 0.909 (CE), 0.745 (GO), 0.908 (SE), and 0.799 (TR). Consequently, each construct in the study was above the recommended range of acceptable values of 0.60 to 0.70 and even higher.

Table 4.9: Reliability Analysis

Variables	Cronbach's alpha (CA)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Customer Experience (CE)	0.907	0.909	0.928	0.683
Grounding (GO)	0.743	0.745	0.886	0.796
Security (SE)	0.897	0.908	0.923	0.706
Trust (TR)	0.797	0.799	0.868	0.621

Source: Developed for the research.

4.4 Partial Least Squares Structural Equation Modelling (PLS-SEM)

4.4.1 Validity Analysis

According to Hair et al. (2014), a construct is considered to explain more than half of the variance of its items if the average variance extracted (AVE) is 0.50 or higher. Table 4.9 presents the AVE ranged from 0.621 to 0.796. All the AVE is higher than the threshold of 0.50. As a result, the constructs in the model are proven to be valid and reliable.

4.4.2 Fornell-Larcker Criterion

The square root of each construct's AVE is greater than the correlations of all data with other latent constructs (Hair et al., 2014). Table 4.10 indicates that the squared root of AVE indicates that there is no association between the constructs. As a result, the constructs in the model are proven to be valid and reliable.

Table 4.10: Fornell-Larcker Criterion

Variables	Customer Experience (CE)	Grounding (GO)	Security (SE)	Trust (TR)
Customer Experience (CE)	**0.826**			
Grounding (GO)	0.627	**0.892**		
Security (SE)	0.555	0.455	**0.840**	
Trust (TR)	0.670	0.635	0.590	**0.788**

Source: Developed for the research.

4.4.3 Factor Loading

According to SmartPLS (n.d.), the threshold value of 0.708, which denotes adequate levels of indicator reliability. Based on the Table 4.11, the factor loadings range is between 0.713 to 0.898. All the items should stay the same. The latent variable, tangible has the smallest of outer loading (0.713), while the GO2 has the highest of outer loading (0.898). Although there were no cross-loading items discovered, the instrument's discriminant validity is supported by the significant loading of all the items on the single factor.

Table 4.11 Item Factor Loading Output

	Outer loadings
CE1 <- Customer Experience	0.834
CE2 <- Customer Experience	0.821
CE3 <- Customer Experience	0.818
CE4 <- Customer Experience	0.801
CE5 <- Customer Experience	0.835
CE6 <- Customer Experience	0.849
GO1 <- Grounding	0.886
GO2 <- Grounding	0.898
LV scores - Credibility -> Service Quality	0.881
LV scores - Empathy -> Service Quality	0.779
LV scores - Reliability -> Service Quality	0.818
LV scores - Responsiveness -> Service Quality	0.729
LV scores - Tangible -> Service Quality	0.713
SE1 <- Security	0.834
SE2 <- Security	0.819
SE3 <- Security	0.820
SE4 <- Security	0.866
SE5 <- Security	0.862
TR1 <- Trust	0.783
TR2 <- Trust	0.782
TR3 <- Trust	0.797
TR4 <- Trust	0.790

Source: Developed for the research.

4.4.4 Heterotrait-monotrait (HTMT) Ratio

According to Henseler et al. (2015), the rigorous criteria need HTMT 0.85. Table 4.12 indicates that the HTMT less than 0.85, range between 0.544 to 0.783, so it is indicated that discriminant validity between a particular pair of reflective constructs has been demonstrated.

Table 4.12: Heterotrait-monotrait Ratio (HTMT)

Variables	**Customer Experience**	**Grounding**	**Security**	**Trust**
Customer Experience				
Grounding	**0.761**			
Security	0.603	**0.544**		
Trust	0.783	0.822	**0.684**	

Source: Developed for the research.

4.4.5 Collinearity Analysis

According to Hair et al (2021), collinearity issues are indicated by VIF ≥ 5. If VIF is less than 3, collinearity is not a concern. Based on Table 4.13 presents the VIF values less than 3, range between 1.630 to 1.675, thus collinearity is not a concern.

Table 4.13: Variance Inflation Factors (VIF)

	VIF
Grounding -> Customer Experience	1.675
Security -> Grounding	1.630
Security -> Trust	1.630
Service Quality -> Grounding	1.630
Service Quality -> Trust	1.630
Trust -> Customer Experience	1.675

Source: Developed for the research.

4.4.6 Path Coefficient Analysis

Bootstrapping is then used to conduct the statistical significance test (Ghorbani et al., 2019). Path weights range from -1 to +1 are standardisation. The strongest and weakest paths are reflected by weights closest to absolute 1 and closest to 0 respectively (Garson, 2016). The correlations found are significant if the t-value in bootstrapping is greater than 1.96 (Ghorbani et al., 2019). The traditional 0.05 threshold for the p value (Leo & Sardanelli, 2020), Table 4.14 indicates that the path coefficient values are positive value and within the range from -1 to +1, means are standardisation. The T-statistics values are greater than 1.96, range between 2.473 to 11.091 and the P values are lower than the 0.05. Consequently, the confidence interval does not cross over 0, within 0.05-0.95, thus, at a 95% confidence level, every variable is statistically significant. All the standard deviation values range between 0.050 to 0.083.

Table 4.14: Path Coefficient Analysis

	Variables	**Path coefficient**	**Standard deviation (STDEV)**	**T statistics**	**P values**	**LCI**	**UCI**
H1	**Service Quality -> Trust**	0.606	0.055	11.091	0.000	0.490	0.704
H2	**Service Quality -> Grounding**	0.471	0.083	5.704	0.000	0.289	0.618
H3	**Security -> Trust**	0.213	0.050	4.251	0.000	0.114	0.307
H4	**Security -> Grounding**	0.162	0.066	2.473	0.013	0.037	0.294
H5	**Trust -> Customer Experience**	0.455	0.053	8.504	0.000	0.344	0.556
H6	**Grounding -> Customer Experience**	0.338	0.059	5.751	0.000	0.219	0.451

Source: Developed for the research.

4.4.7 Mediation Analysis

Table 4.15 indicates that the path coefficient values are positive value and within the range from -1 to +1, means are standardisation. In addition, the T-statistics values are greater than 1.96, range between 2.323 to 6.061 and the P values are lower than the 0.05. Consequently, the confidence interval does not cross over 0, within 0.05-0.95, thus, at a 95% confidence level, every variable is statistically significant. All the standard deviation values range between 0.024 to 0.046.

Table 4.15: Path Coefficient Analysis

	Variables	**Path coefficient**	**Standard deviation (STDEV)**	**T statistics**	**P values**	**LCI**	**UCI**
H7	**Service Quality -> Trust -> Customer Experience**	0.276	0.046	6.016	0.000	0.186	0.365
H8	**Security -> Trust -> Customer Experience**	0.097	0.025	3.920	0.000	0.053	0.150
H9	**Service Quality -> Grounding -> Customer Experience**	0.159	0.045	3.548	0.000	0.078	0.252
H10	**Security -> Grounding -> Customer Experience**	0.055	0.024	2.323	0.020	0.015	0.111

Source: Developed for the research.

4.4.8 Coefficient of Determination (R square)

Based on Table 4.16, the R-square values for this study are 0.517, 0.343, 0.573. 0.517 meaning that the 51.7% of fluctuations in customer experience caused by changes in grounding and trust, while 0.343 meaning that the 34.3% of fluctuations in grounding caused by changes in service quality and security. 0.573 meaning that the 57.3% of fluctuations in trust caused by changes in service quality and security. According to Chin (1998); Höck & Ringle (2010), 0.67, 0.33, and 0.19 are characterised as "substantial," "moderate," and "weak," respectively. All the R-square are above 0.33 is considered moderate.

Table 4.16: R square

Variables	R-square	R-square adjusted
Customer Experience	0.517	0.514
Grounding	0.343	0.339
Trust	0.573	0.571

Source: Developed for the research.

4.4.9 F square

According to Cohen (1988), the f^2 effect sizes of .02,.15, and.35, respectively, correspond to "small," "medium," and "high" effects. Table 4.17 shows the F-square range between 0.025 to 0.528. 0.142 meaning that small effect of grounding on the customer experience. 0.025 meaning that the small effect of security on the grounding, while 0.065 meaning that the small effect of security on the trust. 0.207 meaning that the medium effect of service quality on the grounding, while 0.528 meaning that the high effect of service quality on the trust. 0.256 meaning that medium effect of trust on the customer experience.

Table 4.17: F-square

Variables	F-square
Grounding -> Customer Experience	0.142
Security -> Grounding	0.025
Security -> Trust	0.065

Service Quality -> Grounding	0.207
Service Quality -> Trust	0.528
Trust -> Customer Experience	0.256

Source: Developed for the research.

4.4.10 Q square

Based on the baseline of Q square, Table 4.18 indicates that all the Q square values are more than 0 and there is predictive relevance.

Table 4.18: Q square

Variables	**Q^2predict**
Customer Experience	0.500
Grounding	0.321
Trust	0.553

Source: Developed for the research.

4.5 Conclusion

The research results and analysis that were provided in the previous chapter were the result of extensive investigation. The results are noteworthy because they are consistent with earlier research and provide credence to the constructive connections suggested by the formulated hypotheses. The findings of this investigation and its consequences will be the main topics of the following chapter.

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.0 Introduction

A discussion of the study's limits and consequences will be covered in Chapter 5, along with some suggestions for further research.

5.1 Summary of Major Findings

5.1.1 Description Analysis

This study was based on 334 valid respondents. Majority of them are female respondents are 243 persons, which constitutes 73% of the total. 298 respondents were from the majority age group of 18-25 years old, which constitutes 89.2% of the total. In addition, 98% of the respondents are Chinese which constitutes 312 of them, then followed by 12 Indian, 8 Malay, 1 Kadazan and 1 Korea. Most of the respondents have completed bachelor's degree (82.3%). Most of them are getting below RM500 per month as income (152), which comprises 46% of the total. Majority of them used ChatGPT (55%). Lastly, 29.4% respondents choose fast response and 24/7 customer service as their reason is the highest among other reasons.

5.1.2 Reliability Analysis

All of the variables in the study had reliability scores greater than 0.7. Every variable included in the study is reliable. As a result, the factors in the study were trustworthy and allowed the research to move on to the following phase.

5.1.3 Partial Least Squares Structural Equation Modelling (PLS SEM) Analysis

Moreover, AVE values are above the threshold of 0.50, ranged from 0.621 to 0.796. The HTMT values are less than 0.85, range between 0.544 to 0.783. The VIF values are less than 3, range between 1.630 to 1.675, thus collinearity is not a concern. The path coefficient values are positive value. In addition, the T-statistics values are greater than 1.96, range between 2.473 to 11.091 and the P values are lower than the 0.05. Consequently, the confidence interval does not cross over 0. All the standard deviation values range between 0.050 to 0.083. For the mediation analysis, the path coefficient values are positive value. In addition, the T-statistics values are greater than 1.96, range between 2.323 to 6.061 and the P values are lower than the 0.05. Consequently, the confidence interval does not cross over 0. All the standard deviation values range between 0.024 to 0.046. The R-square values for this study are 0.517, 0.343, 0.573. All the R-square are above 0.33 is considered moderate. F-square range between 0.025 to 0.528. 0.142, 0.025, 0.065 are small effect. 0.207, 0.256 are medium effect. 0.528 is high effect.

5.2 Discussion of Major Finding

Table 4.19 Discussion of Major Findings

	Hypothesis	Result	Decision
H1	**Service quality has positive effect on trust.**	p = 0.000 (0.490-0.704)	Supported
H2	**Service quality has positive effect on grounding.**	p = 0.000 (0.289-0.618)	Supported
H3	**Security has positive effect on trust.**	p = 0.000 (0.114-0.307)	Supported
H4	**Security has positive effect on grounding.**	p = 0.013 (0.037-0.294)	Supported
H5	**Trust has positive effect on customer experience.**	p = 0.000 (0.344-0.556)	Supported
H6	**Grounding has positive effect on customer experience.**	p = 0.000 (0.219-0.451)	Supported
H7	**Trust mediates the relationship between service quality and customer experience.**	p = 0.000 (0.186-0.365)	Supported
H8	**Trust mediates the relationship between security and customer experience.**	p = 0.000 (0.053-0.150)	Supported
H9	**Grounding mediates the relationship between service quality and customer experience.**	p = 0.000 (0.078-0.252)	Supported
H10	**Grounding mediates the relationship between security and customer experience.**	p = 0.020 (0.015-0.11)	Supported

Source: Developed for the research.

H1: Service quality has positive effect on trust.

Given that its P-value is less than 0.05, hypothesis 1 was approved for this study. A strong correlation was found between service quality and trust. The AI-Chatbot service quality affects customer trust is corroborated by the study (Shahzad et al., 2024). The significance of AI-Chatbot service quality has also been extensively studied in the information technology literature, considering factors like user trust, performance, and satisfaction (Li et al., 2023). This study demonstrated that good service quality of AI-Chatbot, customers experience will likewise increase.

H2: Service quality has positive effect on grounding.

Given that its P-value is less than 0.05, hypothesis 2 was approved for this study. A strong correlation was found between service quality and grounding. The significance of grounding behaviors for successful communication, which is necessary for task-dependent applications of socially interactive agents, was emphasized by the researchers by manipulating embodiment and failure variables in conversational agents during guided tasks (Kontogiorgos et al., 2021). The design of conversational agents (AI-Chatbot) has a major impact on their capacity to create shared understanding (grounding), especially in the areas of embodiment (voice, appearance) and failure management (errors, misunderstandings). Good service quality promotes customer engagement and a satisfying experience by improving communication and task execution. This study demonstrates that when customers feel more understood, better service quality has a good impact on grounding.

H3: Security has positive effect on trust.

Given that its P-value is less than 0.05, hypothesis 3 was approved for this study. A strong correlation was found between security and trust. Users' faith in the safe and moral management of their data is at the center of the privacy risk related to trust (Gumusel et al., 2024). For successful adoption of AI-Chatbots, customer trust must be upheld and privacy concerns must be addressed. Maintaining consumer trust and confidence in AI-Chatbots and ensuring their appropriate and ethical use will become more crucial as these systems proliferate across a range of businesses. Ultimately, developers address AI-Chatbot security holistically, considering user trust, privacy, and ethical issues in addition to technological security measures (Yang et al., 2023). As a result, this study proves that the security of AI-Chatbot has significantly positive effect on trust and supported by these studies.

H4: Security has positive effect on grounding.

Given that its P-value is less than 0.05, hypothesis 4 was approved for this study. A strong correlation was found between security and grounding. Gumusel et al. (2024) point out that putting security first moves the conversation away from just talking about the advantages of AI-Chatbots and toward managing privacy responsibly, which eventually increases user trust and improves the quality of interactions. Robust security measures improve user confidence and engagement, which has a favorable effect on AI-Chatbot grounding. Privacy and security are still major concerns, even with the advantages of data harvesting for personalization. By addressing these, interaction's quality is improved, which facilitates clear communication and understanding between parties.

H5: Trust has positive effect on customer experience.

Given that its P-value is less than 0.05, hypothesis 5 was approved for this study. A strong correlation was found between trust and customer experience. The psychological aspects that could influence whether an intelligent recommendation agent's counsel is accepted are examined by the authors. Trust will reduce reactive behavior and increase acceptance (Aljukhadar et al., 2017). By boosting acceptance of AI-Chatbot recommendations, decreasing resistance, and encouraging contentment and loyalty, trust improves the customer experience. This study proves that trust has positive effect on customer experience.

H6: Grounding has positive effect on customer experience.

Given that its P-value is less than 0.05, hypothesis 6 was approved for this study. A strong correlation was found between grounding and customer experience. Communication success is based on mutual understanding amongst all parties participating in the communication process (Wang et al., 2022). Current study proves that by improving the customer experience requires grounded communication that ensures understanding. It creates smooth relationships, decreases miscommunications, and increases trust. AI-Chatbots, for example, validate user input and customize responses to produce individualized experiences.

H7: Trust mediates the relationship between service quality and customer experience.

Given that its P-value is less than 0.05, hypothesis 7 was approved for this study. As a mediator between the user and technology, trust increases the likelihood that users will reveal personal information or engage activities (Gefen et al., 2003). Users likely to believe that an AI-Chatbot provides high-quality service when they have a positive interaction with it. Customers' trust in AI-Chatbots is increased when they receive consistent, accurate, and beneficial responses (Shahzad et al., 2024). Thus, the effectiveness and satisfaction of a customer's interaction with an AI-Chatbot in meeting their needs is a crucial aspect of its experience (Pizzi et al., 2020). Through the above article, customer experience tends to increase based on AI-Chatbot service quality and building trust. Current study supported by these articles and proved that trust mediates the relationship between service quality and customer experience.

H8: Trust mediates the relationship between security and customer experience.

Given that its P-value is less than 0.05, hypothesis 8 was approved for this study. To protect the user's data, AI-Chatbot’s secure communication is crucial (Hasal et al.,2021). Regarding trusting technology-mediated services, there are now two lines of inquiry: trust in the technology (Ghazizadeh, Lee, & Boyle, 2011) and trust in the cutting-edge company's procedures and communication (Nienaber & Schewe, 2014). Through these studies, the security of AI-Chatbots is important to provide secure communication. When AI-Chatbots improve customer satisfaction by delivering consistently, customers trust them. This study demonstrates that trust mediates the relationship between security and customer experience.

H9: Grounding mediates the relationship between service quality and customer experience.

Given that its P-value is less than 0.05, hypothesis 9 was approved for this study. For AI-Chatbot and customers to communicate, grounding refer to both linguistically and non-linguistically is a fundamental step to guarantee exchanges stay pertinent and logical. Customers demand AI-Chatbots to retain a constant state of grounding, even though AI-Chatbots are nonhuman, which is difficult to accomplish reliably. Gathering customer grounding information becomes essential from a business standpoint to improves the service quality by enabling the AI to respond in a tailored and contextually relevant manner (Jeon, 2024). A more positive customer experience is subsequently fostered by this improved service since interactions feel more natural and in line with customer expectations. The technological prowess of AI systems is thus linked to the human-centered objectives of high service quality and exceptional customer experience through the mediating role of grounding.

H10: Grounding mediates the relationship between security and customer experience.

Given that its P-value is less than 0.05, hypothesis 10 was approved for this study. This study suggests that trust and grounding operate as mediators in the relationship between consumers' identification with AI-Chatbots and suggestions for real brand purchases (Jeon, 2024). This study similar with current study indicates that grounding mediates the relationship between security and customer experience. To protect the user's data, secure communication with the AI-Chatbot is crucial (Hasal et al., 2021), This study proves that grounding in AI communication by ensuring customers feel understood, which enhances their confidence in the system's security.

5.3 Implications of Study

5.3.1 Practical Implications

This study emphasizes how important AI-Chatbot service quality and security is for building customer trust and grounding. Due to their importance as mediators, trust and grounding are given top priority by businesses and technology developers. Customer trust, grounding, and the entire customer experience are all improved by robust security and first-rate customer service through this research. Based on the tasks they do, customers have varying opinions of AI-Chatbots. Since relying too much on generic solutions can erode trust and grounding, businesses should place a higher priority on professional competencies, excellent service, and efficient issue resolution. Striking a balance between security and functionality can increase trust and grounding.

Customers appreciate AI-Chatbot's high service quality and robust security. Retailers who want to implement AI-Chatbot must first understand how customers feel about them and how they affect the customer experience. This study highlights important elements for successful retail strategies, such as AI-Chatbot security and service quality. To solve issues like the lack of a human touch in AI-Chatbot, retailers and AI developers should work together. Integrating AI-Chatbots requires customer trust. Businesses must prioritize ongoing learning and adaptation considering the rapid improvements in AI-Chatbot if they want to remain competitive and satisfy changing customer demands.

5.3.2 Theoretical Implications

From an academic perspective, this paper makes several theoretical advances. First, by applying the SOR framework to the AI-Chatbot in the context of mobile apps and digital marketing, this study advances it. Traditional situations were the primary focus of the SOR framework in the past (Kamboj et al., 2018; Kim et al., 2020). By examining certain characteristics of AI-Chatbots and how they shape consumers' trust, sense of security, and customer experience in the context of mobile apps and digital marketing, this expansion adds to the SOR framework. Additionally, the research's theoretical model adds to the body of knowledge on information systems.

In conclusion, this research offers a more profound comprehension of the AI-Chatbot's user experience. The efficient use of automated AI-Chatbots is a major concern, particularly in determining the direction of digital marketing, as this new and developing technology offers businesses and consumers an increasing number of advantages. This study contributes to our knowledge of customers' trust and confidence in AI-Chatbots.

5.4 Limitations of Study

As with all studies, it is important to acknowledge and consider the limitations of this one when interpreting its findings and conducting additional research. Particularly in the customer service industry, there is a difference between humans and machines. This study solely looked at AI-Chatbots in general industry. Furthermore, the traits of the clients may also influence how they accept or see the AI-Chatbot. Furthermore, this study's data collection is mainly from female and Chinese which indicates that it is limited to a diverse demographic profile. According to current research, trust, service quality, security, and grounding are critical success characteristics for AI-enabled customer interactions from the perspective of the consumer. This suggests that a retail organization may adopt a lack of these success factors. Furthermore, most of the participants are in the 18–25 age range. Additionally, this study employed a quantitative self-reported approach indicates that lack of diverse perspectives. Furthermore, the suggested study model incorporates only a small number of variables and is predicated on the SOR notion.

The limitations are acknowledged but they do not detract from the significance of findings but merely provide platforms for future research.

5.5 Recommendation of Future Study

The distinction between human and automated customer support representatives should be further explored in future studies. Future research can be conducted in specific industries that may differ from general industries (such as healthcare or the sharing economy). Other sectors and merchants may be the subject of future research. The results of a future study that is advised to be conducted in a different industry may differ. Future research should take customer traits into account. Other Big Five personality traits (Fiske, 1949) could be examined by future investigations as they might have a greater impact on AI-Chatbot adoption.

Moreover, future research can be conducted in diverse demographic profiles. The implementation of each of these success characteristics in a retail organization should be the focus of future research. Examining AI technology's security and ethics from a consumer standpoint offers further study opportunities. Given the greater technological familiarity of younger generations, an older sample may yield different findings. Therefore, current study propose to repeat the study with additional volunteers of various ages. Lastly, in-depth qualitative research, including interviews, is necessary for future studies to gather diverse perspectives. To improve the model's capacity for explanation, future research must incorporate additional relevant variables.

5.6 Conclusion

Lastly, every day in the online world, customers interact with AI-enabled technology, where AI becomes "the other" that they speak to daily. This study adds to our understanding of how AI-Chatbot impacts customer grounding and trust and how it impacts customer experiences. The study's results provide empirical support for marketers who heavily spend in attempts to make their AI-Chatbot more human-like by confirming that it has an impact on customers' confidence and sense of security. In addition to improving the theoretical understanding of customer experience in online environments, the study adds to the body of research by quantifying how AI-Chatbot can impact not only customer experience but also customers' trust and grounding. The findings also have practical implications, as they clearly show how marketers can use AI-Chatbot as a tool in their marketing strategies. The finding has theoretical implications, as adds to the body of knowledge on information systems.

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APPENDIX

Appendix 3.1: Questionnaire

A Study on the Relationship Marketing Affecting the Customer Experience in Using AI-Chatbot

Dear respondent,

I am a second-year undergraduate student of International Business, from University Tunku Abdul Rahman (UTAR). The purpose of this survey is to study the relationship marketing affecting the customer experience in using AI-Chatbot. An artificial intelligence (AI) tool called a chatbot is created to mimic human communication. The artificial intelligence (AI) chatbot is emerging as a significant corporate customer-facing application, potentially increasing customer service efficiency while reducing costs.

Thank you for your participation.

Instruction:

1. There are SIX (6) pages in this questionnaire. Please answer ALL questions which are needed in ALL pages.
2. Completion of this questionnaire will take you approximately 5 to 10 minutes.
3. The content of this questionnaire will be kept strictly confidential and will be used only for academic research purpose.

Section A: Demographic Profile

In this section, we are interested in your background in general. Kindly mark your response, which will be treated with the utmost confidentiality.

1. Gender :
   - ☐ Male
   - ☐ Female

2. Age :
   - ☐ Below 18 years old
   - ☐ 18 - 25 years old
   - ☐ 26 - 35 years old
   - ☐ 36 - 45 years old
   - ☐ 46 – 55 years old
   - ☐ Above 55 years old

3. Ethnicity :
   - ☐ Chinese
   - ☐ Malay
   - ☐ India
   - ☐ Others

4. Level of Study :
   - ☐ UEC /STPM /A-Level /Foundation
   - ☐ Diploma
   - ☐ Bachelor's Degree
   - ☐ Master's Degree
   - ☐ Doctorate Degree

5. Monthly Income :
   - ☐ Below RM500
   - ☐ RM500 - RM1000
   - ☐ RM1001 - RM2000
   - ☐ RM2001 - RM3000
   - ☐ RM3001 - RM4000
   - ☐ Above RM4000

4. Do you currently use any AI-Chatbot related products?

- [ ] Yes
- [ ] No

5. Which AI-Chatbot have you used before? (Can choose more than one)

- [ ] ChatGPT
- [ ] Google Gemini
- [ ] Microsoft Copilot
- [ ] Perplexity .ai
- [ ] Others

6. Why do you often use AI-Chatbot? (Can choose more than one)

- [ ] Fast response and 24/7 customer service
- [ ] Provide personalized response
- [ ] Provide easy-to-use self-service choices
- [ ] Support for multiple languages

Section B: Evaluate the Factors Affecting Customer Experience in Using AI-Chatbot

Note: Scale 1 indicates that you strongly disagree with the statement and 5 indicates you strongly agree with the statement

[Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5]

Subsection 1: Service Quality

Reliability	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot is useful.	1	2	3	4	5
2. AI-Chatbot is reliable.	1	2	3	4	5
3. AI-Chatbot gives useful information.	1	2	3	4	5
4. AI-Chatbot gives real information.	1	2	3	4	5

Responsiveness	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot responds quickly.	1	2	3	4	5
2. AI-Chatbot responds immediately.	1	2	3	4	5

Empathy	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot is sympathetic.	1	2	3	4	5
2. AI-Chatbot is honest.	1	2	3	4	5
3. AI-Chatbot is attentive.	1	2	3	4	5

Credibility	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot is credible.	1	2	3	4	5
2. AI-Chatbot is impartial.	1	2	3	4	5

3. AI-Chatbot is well-informed.	1	2	3	4	5
4. AI-Chatbot is qualified.	1	2	3	4	5
5. AI-Chatbot is an expert.	1	2	3	4	5

Tangibles	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot has attractive Messenger colours.	1	2	3	4	5
2. AI-Chatbot has attractive website colours.	1	2	3	4	5
3. AI-Chatbot has an attractive appearance.	1	2	3	4	5

Subsection 2: Security

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. I feel safe in my interaction when using AI-Chatbot.	1	2	3	4	5
2. I feel my privacy is protected by AI-Chatbot.	1	2	3	4	5
3. I trust that AI-Chatbot will not misuse my personal information.	1	2	3	4	5
4. I feel I can trust AI-Chatbot.	1	2	3	4	5
5. AI-Chatbot instills confidence in me.	1	2	3	4	5

Section C: Evaluate the Effect of Service Quality and Security of AI-Chatbot on Consumer

Note: Scale 1 indicates that you strongly disagree with the statement and 5 indicates you strongly agree with the statement

[Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5]

Subsection 1: Trust

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot engages me.	1	2	3	4	5
2. AI-Chatbot puts my interests first.	1	2	3	4	5
3. AI-Chatbot keeps its promises.	1	2	3	4	5
4. AI-Chatbot gives perfect service quality.	1	2	3	4	5

Subsection 2: Grounding

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. AI-Chatbot provided feedback on having accepted my input.	1	2	3	4	5
2. I felt that AI-Chatbot understood what I had to say.	1	2	3	4	5

Section D: Evaluate the Customer Experience in Using AI-Chatbot

Note: Scale 1 indicates that you strongly disagree with the statement and 5 indicates you strongly agree with the statement

[Strongly disagree = 1, Disagree = 2, Neutral = 3, Agree = 4, Strongly agree = 5]

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
1. I am satisfied with the AI-Chatbot.	1	2	3	4	5
2. I am content with the AI-Chatbot.	1	2	3	4	5
3. The AI-Chatbot did a good job.	1	2	3	4	5
4. The AI-Chatbot did what I expected.	1	2	3	4	5
5. I am happy with the AI-Chatbot.	1	2	3	4	5
6. I was satisfied with the experience of communicating with the AI-Chatbot.	1	2	3	4	5

Appendix 3.2: Letter of Ethical Clearance

UNIVERSITI TUNKU ABDUL RAHMAN DU012(A)
Wholly owned by UTAR Education Foundation Co. No. 578227-M

Re: U/SERC/78-352/2024

9 September 2024

Dr Fitriya Binti Abdul Rahim
Head, Department of International Business
Faculty of Accountancy and Management
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Dr Fitriya,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of International Business (Honours) programme enrolled in course UKMZ3016. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	Strategic Approaches to Enhance Consumer Engagement and Traction Through Livestreaming Content: A Comparative Analysis of Effective Tactics and Best Practices	Adeline Kong Qing Qing	Pn Ezatul Emilia Binti Muhammad Arif	9 September 2024 – 8 September 2025
2.	Factors Influencing Customers Acceptance of Malaysian Traditional Bank's Digital Channels	Chan Huey Teng	Dr Tee Peck Ling	
3.	Relationship Marketing Affecting the Customer Experience in Using AI-Chatbot	Chan Pei Yee	Dr Yeong Wai Mun	
4.	Factors that Influence Employee Performance in the Workplace	Chen Kar Him	Dr Komathi a/p Munusamy	
5.	Social Media Advertising Format that Affect Consumer Behaviour in Malaysia	Cheong Yi Qian	Dr Fok Kuk Fai	
6.	Consumer Intentions to Switch Accommodations from Traditional Hotels to Airbnb	Chia Rong Wei	Dr Law Kian Aun	
7.	Engulfed by Recommendation Systems: Walking Away Empty-handed Becomes a Challenge	Chin Kai Ning	Pn Ezatul Emilia Binti Muhammad Arif	
8.	The Interrelations Between Artificial Intelligence (AI) Usage and Academic Performance	Chin Wie Jane	Dr Low Mei Peng	
9.	Factor Affecting University Students' Behavioural Intention to Use ChatGPT for Academic Purpose	Chock Yee Fai	Pn Farida Bhanu Binti Mohamed Yousoof	
10.	The Impact of ESG Initiatives on Green Product and Consumer Purchase Intentions	Choi Yoon Qi	Dr Foo Meow Yee	
11.	Factors Influencing Gender Entrepreneurial Intention Among Malaysian Undergraduate Students	Chong Chean You	Dr Kalaivani a/p Jayaraman	
12.	The Influence of Technological Infrastructure on the Success of Digital Reading Platforms Globally Among Students	Chong Li Xian	Dr Komathi a/p Munusamy	

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Tel: (603) 9086 0288 Fax: (603) 9019 8868
Website: www.utar.edu.my

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
13.	The Impact of Social Sustainability Awareness on Consumer Buying Behavior	Fang Yu Mei	Dr Komathi a/p Munusamy	9 September 2024 – 8 September 2025
14.	The Effect of Social Media Influencer Marketing on the Purchase Intention of Young Consumers in the Skincare Product Industry	Foh Zhi Hui	Ms Goh Poh Jin	
15.	University Student's Intention to Adopt Mobile Payments in Malaysia	Foo Yong Yi	Pn Farida Bhanu Binti Mohamed Yousoof	
16.	Modernisation and Transformation in SMEs: A Case Study Exploring Owner Perspectives on Process Transformation and Technological Adaptation	Grace Lim Wei Qi	Mr Lee Yoon Heng	
17.	Understanding the Influence of Greenwashing on Green Brand Equity and Green Purchase Intention Among Electric Vehicle Consumers in Klang Valley	Heng Xian Wei	Dr Tan Pei Meng	
18.	Adoption of Digital Marketing on SME Service Sector in Klang Valley	Jordan Wue Bin Hassan Wue	Ms Puvaneswari a/p Veloo	
19.	Exploring Determinants of Malaysian Purchase Intention for Electric Vehicles	Joyce Yap Jie Ni	Dr Malathi Nair a/p G Narayana Nair	
20.	Sustainable Shopper: Linking ESG with the Shopping Carts	Julia Look Hui Sian	Dr Abdullah Sallehhuddin Bin Abdullah Salim	
21.	Investigating Influential Factors on Female Consumers' Purchase Behavior or Organic Perfumes in Malaysia	Kang Karen	Dr Ooi Bee Chen	
22.	Factors Influencing Consumer Purchase Intention Towards Green Household Products	Kok ZiLi	Dr Ooi Bee Chen	
23.	Winning in Cross-border E-commerce: Factors That Influence Strategic Platform-based Product Selection Among Sellers	Lai Kah Shen	Pn Ezatul Emilia Binti Muhammad Arif	
24.	Employee Retention's Impact Factors Within the Retail Industry	Lee Yee Hong	Dr Foo Meow Yee	
25.	Factors Influencing the Employee Turnover Rate Among Fresh Graduate Employees	Leong Weng Kent	Dr Kalaivani a/p Jayaraman	
26.	The Factors Influencing the Purchase Intention of Electric Vehicles Among Malaysian Young Adults	Lew Hui Ching	Dr Foo Meow Yee	
27.	Exploring Factors Influencing Customer Loyalty in Malaysia's Traditional Coffee Shop (Kopitiam)	Lew Zhi Qing	Dr Malathi Nair a/p G Narayana Nair	
28.	Green Purchase Intention Towards Reusable Shopping Bag in Malaysia	Lim Khang Xian	Ms Tai Lit Cheng	
29.	What Type of E-commerce Advertising Method Impact Customer Purchase	Lim Qi Yi	Pn Ezatul Emilia Binti Muhammad Arif	
30.	Unlocking Cross-Border Growth: Exploring Digital Free Trade Zones' Impact on International Trade	Lim Ying Ze	Pn Ezatul Emilia Binti Muhammad Arif	
31.	Consumer Behavior Trends and Preferences in the Malaysia Car Spare Parts Market: A Case Study of Perodua Bezza	Loh Eng Kang	Dr Fok Kuk Fai	
32.	Impact of Sustainable Packaging on Consumer Buying Behaviour in Malaysia	Loh Yan Min	Dr Fok Kuk Fai	
33.	Explicating the Influence of Artificial Intelligence (AI) Literacy on Employee Performance	Loke Li Ying	Dr Low Mei Peng	
34.	Leveraging Artificial Intelligence (AI) Competencies for Organisational Performance	Loke Xin Yu	Dr Low Mei Peng	
35.	The Influence of Culture on Consumer's Intention to Purchase Personalized Products	Loo Ci Ting	Dr Choo Siew Ming	
36.	Exploring The Financial Benefits and Risks of Allocating Additional Income Towards Investment Opportunities	Loo Su Yu	Dr Choo Siew Ming	
37.	Factors Influencing Consumer's Purchase Behaviour Towards Organic Food Among Malaysian University Students in Klang Valley	Low Chan Guan	Dr Ooi Bee Chen	
38.	Adoption AI in Logistics Industry: Improved Efficiency and Fault Tolerance	Low Sam Yee	Mr Khairul Anuar Bin Rusli	

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
39.	Impact of Digital Marketing Strategy on Purchase Intention	Lum Jia Mei	Dr Komathi a/p Munusamy	9 September 2024 – 8 September 2025
40.	Unveiling the Elements of Employee Motivation for Thriving Workplaces in Malaysia	Michelle Tan Hui Shan	Dr Kalaivani a/p Jayaraman	
41.	Women's Entrepreneurship Success in the Technological Industry	Ooi Xin Yi	Dr Law Kian Aun	
42.	Social Media Strategies for Business Success Maximizing Impact through Navigating Channels and Engaging Audiences	Poon She Kei	Pn Ezatul Emilia Binti Muhammad Arif	
43.	Measuring the Impact of Organizational Factors on Turnover Intention of Fast-Food Industry Employees in Malaysia	Rachel Ong Pei Lyn	Ms Puvaneswari a/p Veloo	
44.	Impact of Transformational and Authentic Leadership on Innovation in Higher Education in Malaysia: The Contingent Role of Trust in Leader	Robin Wong Woon Ping	Ms Puvaneswari a/p Veloo	
45.	Social Media Influencers on Consumer Purchase Intention: The Sportswear Products	Sam Yu Xiang	Dr Sia Bee Chuan	
46.	The Influence of Customer Relationship Management on Customer Loyalty in Insurance Sector	Seah Chee Keong	Dr Komathi a/p Munusamy	
47.	Impact of Social Media Influencers (SMIs) on Purchase Intention of Young Adults in Malaysia	Seow Gin See	Dr Foo Meow Yee	
48.	Understanding University Student's Behavioral Intention in using 'Smart Technology'	Sin Chee Leong	Ms Goh Poh Jin	
49.	The Challenge of Consumer Adoption of Battery Electric Vehicle (BEV) in Malaysia	Siow Huang Ming	Dr Sia Bee Chuan	
50.	Customer Motivation in Choosing Preferred Courier Service	Syamini Syazwani Devi A/P Muraleidaran	Dr Komathi a/p Munusamy	
51.	Digital Platform: Do Data Privacy Concerns and Transparency Affect User's Trust and Loyalty?	Tai Buo Ting	Pn Ezatul Emilia Binti Muhammad Arif	
52.	A Study of the Impact of Flexible Work Arrangement on Employees' Turnover Intention Among Generation Z in Klang Valley	Teh Jia Chuen	Dr Lee Siew Peng	
53.	The Role of E-training, E-compensation and E-recruitment in Enhancing Employee Productivity in International Companies in Malaysia	Teo Wen Ping	Dr Omar Hamdan Mohammad Alkharabsheh	
54.	Factors Influencing the Sustainable Tourism Intentions Among Generation Z in Malaysia	Tey Xin Tong	Dr Tiong Kui Ming	
55.	Motivation Factors Impact the Employee Performance in the Retail Industry in Malaysia	Thiang Zhen Wu	Dr Law Kian Aun	
56.	Factors Motivating Malaysian Consumers' Intention Using QR Code Payment when Purchasing Movie Tickets	Wang Kean Seng	Pn Faridah Hanum Binti Amran	
57.	Entrepreneurial Orientation Relationship with Firm Performance Among F&B Industry: Perspective of Malaysian SME	Wong Chean Huai	Mr Mahendra Kumar a/l Chelliah	
58.	Resilience of Global Challenges: A Study of Manufacturing Resilience in Malaysian Manufacturing Industry	Wong Jin Mun	Dr Law Kian Aun	
59.	Impact of Customer Service Automation on the Performance of Customer Relationship Management in the Retail Sector	Yap Pui Man	Dr Law Kian Aun	
60.	The Influence of Social Media Marketing on Purchase Intention of Sportswear Among Malaysian Youth	Yap Seng Fui	Ms Cheah Lee Fong	
61.	Impact of Social Media Marketing on Consumer Purchase Intention in Food and Beverage Industry in Malaysia	Yee Kar Hung	Dr Sia Bee Chuan	
62.	Exploring the Relationship Between Organizational Culture and Customer Retention in E-commerce: A Study of Online Shoppers	Yeoh Chin Hui	Dr Choo Siew Ming	
63.	Factors Affecting Patient Satisfaction on Service Quality: An Investigation of Government Hospital in Klang Valley	Yoong Pooi Lim	Dr Tey Sheik Kyin	

No.	Research Title	Student's Name	Supervisor's Name	Approval Validity
64.	The Connection Between Gig-Economy Employees and Personal Well-Being	Yu Kay Ciek	Dr Law Kian Aun	9 September 2024 – 8 September 2025
65.	Role of Brand Communities in Building Brand Loyalty	Yuvarani a/p Suresh	Dr Komathi a/p Munusamy	

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

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Chairman
UTAR Scientific and Ethical Review Committee

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