AI-CHATBOT APPLICATION AS AN E-SERVICE AGENT TO DEVELOP A CUSTOMER-BRAND RELATIONSHIP

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ABSTRACT

This dissertation explores AI chatbots as e-service agents in developing customer-brand relationships. Chapter II presents a bibliometric analysis of 571 papers (2005–2022), identifying key research trends and academic clusters in computer science, marketing service, and digital health.

Chapter III develops a conceptual framework using the Technology Acceptance Model (TAM) and A-B-C model of attitudes, examining how interaction, perceived enjoyment, customization, and problem-solving influence customer perceptions, satisfaction, and trust.

Chapter IV empirically validates chatbot effectiveness through a mixed-methods approach, confirming that perceived ease of use and usefulness drive positive attitudes and brand loyalty. AI chatbots enhance customer engagement while reducing human intervention.

This study extends TAM with chatbot-specific attributes, providing theoretical and practical insights for businesses. It highlights AI transparency and ethical considerations as key to trust-building and emphasizes AI's role in sustainable digital transformation and long-term brand engagement.

KEY WORDS: AI chatbot / Service agent marketing effort / Attitude / Customer-brand relationship / TAM

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CHAPTER I
INTRODUCTION

Artificial intelligence (AI), often known as machine learning, has facilitated innovation in many business industries, such as digital medicine, education computing, and marketing services. AI technology is widely used by businesses to improve customer experience, grow revenue, and save operational expenses to shape their branding have predicted that AI business can contribute $15.7 trillion to the world economy. Similarly, large investments in AI firms have risen tremendously from $1.3 billion to $40.4 billion worldwide in the past few years. In the next couples years, firms are expected to expand globally with AI.

One of the AI applications many businesses adopt is an e-service chatbot, which has picked up the fastest pace in recent years. In general, there are two types of e-service chatbots: a) rule-based chatbots and b) AI-powered chatbots. Rule-based chatbots are commonly known as decision-tree bots. The rule-based chatbot functions based on the input, following a fixed set of rules. They employ a set of predetermined principles, as implied by their name. These criteria serve as the foundation for the categories of problems the chatbot is knowledgeable about and can answer. The responses of this type of chatbot depend on the customer input. The AI-powered chatbot, however, actively learns from interactions, which will improve future performance. Customers can communicate with AI-powered chatbots anytime and anywhere. Instead of a one-way purchase, human-computer interaction theory proposes a new model for firms to create a deeper relationship with customers through continuing and tailored "dialogues". AI chatbots are designed to communicate with humans or possibly replace human agents in digital marketing due to continual developments in AI replicating normal language.

Alipay is one of the most widely used digital platforms in China, offering an extensive range of financial and lifestyle services through its “super app” ecosystem. The Alipay AI chatbot, integrated into the app’s customer service module, is designed to assist users with routine tasks and inquiries across a variety of service categories. These include, but are not limited to, payment confirmations, transaction record queries, account security alerts, and general technical support. The chatbot is accessible 24/7 and utilizes natural language processing to respond to both structured and unstructured queries. It often serves as the first point of contact before escalation to human agents. In this study, the chatbot is examined in its role as a service interface, providing functional and communicative interactions that potentially influence users' perceptions, satisfaction, and trust toward the Alipay brand.

To reach the overall goal of this thesis and to investigate how a brand can devise a chatbot to nurture its customer-brand relationship, this research has set up the following questions:

1) How can Ailpay chatbot facilitate customer-brand relationship development in terms of satisafaction, brand trust, and commitment?

2) How do Ailpay chatbot characteristics antecedents in terms of interaction, perceived enjoyment, customization, and problem-solving affect customers' perception of TAM (perceived usefulness & percevied ease of use), HRI (percevied trust) towards the use of the chatbot?

3) How do customers' perceptions of TAM (perceived usefulness & percevied ease of use), HRI (percevied trust) towards the Ailpay chatbot induce their affective responses?

4) What is the role of customer attitude towards the Ailpay chatbot in customer-brand relationship development?

This study adopts a mixed-methods approach, combining qualitative exploration with quantitative validation to provide a comprehensive understanding of how AI chatbots, as e-service agents, influence customer–brand relationships. The research begins with a qualitative phase involving semi-structured interviews to explore user experiences and identify relevant chatbot characteristics that shape perception and engagement. These insights inform the development of a conceptual model, which is subsequently tested in a quantitative phase using a structured survey and Structural Equation Modeling (SEM). This methodological design is appropriate for addressing the research objectives, as it allows for both contextual exploration and empirical testing. The integration of qualitative and quantitative data ensures that the model is grounded in real-world user experiences while offering statistical rigor to validate the proposed relationships. This sequential design enhances the validity and reliability of the findings and aligns with the goal of capturing the cognitive, affective, and behavioral dimensions of chatbot interaction in a digital service context.

In this study, the researchers based on the bibliometric analysis to find who are the most influential authors and which are the top documents cited by other researchers. The researchers can find the related papers from the bibliometric analysis. Then, it helps the researchers build own conceptual frameworks as the bibliometric analysis can provide related studies. The authors can study the related theories based on the bibliometric analysis to write the conceptual paper. Last, the researchers used a mixed methodology to test the relationship. Here are the structure of this thesis.

This Ph.D. dissertation consists of three main chapters focusing on AI-chatbot application as an e-service agent to develop a customer-brand relationship. The three chapters are:

Chapter II: A Bibliometric Review of Analyzing the Intellectual Structure of the Knowledge Base on AI Chatbot Application from 2005–2022

Chapter III: Conceptualizing AI-Chatbot Application as An E-Service Agent to Develop A Customer-Brand Relationship

Chapter IV: Navigating the Digital Frontier: Exploring the Dynamics of Customer-brand Relationships through AI Chatbots

Chapter II study a bibliometric review of artificial intelligence chatbot applications from a new perspective. With the development of innovation, many firms are using artificial intelligence chatbots to manage their business and build customer relationships. Thus, this study aims to offer bibliometric assessments of the expanding literature about AI chatbot services. We used the VOS Viewer software to analyze the data based on Scopus from 2005 to 2022. We extracted and examined the data from several AI chatbot service bibliometric reviews. Given the data, we form 571 peer-reviewed papers from the journal. After analyzing the data, the researchers found the most influential work, authors, and co-cited authors on AI chatbots. Similarly, the researchers, based on the author’s co-citation analysis and the intellectual structure, distinguish between “computer science,” “chatbot service,” and “digital health.” Computer science is the most critical discipline regarding AI applications. This review paper was published in the *Journal of Information Systems Engineering and Management* (Xia et al., 2023).

Chapter III mainly introduces the concept of an AI chatbot application as an E-service agent to develop a customer-brand relationship. A conceptual paper aimed to explore the application of AI chatbots as e-service agents—specifically in terms of interaction, perceived enjoyment, customization, and problem-solving capabilities—and their impact on customer-brand relationships by enhancing customers' positive attitudes. To achieve this, the research employs the Technology Acceptance Model (TAM), focusing on two key indicators: perceived ease of use and perceived usefulness. These factors help clarify how the unique characteristics of chatbots influence customer-brand relationships. Data for this study were gathered from existing theoretical and empirical research. Using the A-B-C model, which includes cognitive (thinking), affective (feeling), and behavioral (doing) components, the conceptual framework examines how external factors—interaction, perceived enjoyment, customization, and problem-solving capabilities—significantly impact perceived ease of use, perceived usefulness, customer attitudes, and ultimately, customer-brand relationships. Additionally, perceived ease of use and usefulness significantly correlate with customer attitudes and brand relationships. The study also highlights the affective component of attitude as a key predictor of customer-brand relationship outcomes. This study was published in *Operational Research in Engineering Sciences: Theory and Applications* (Xia & Shannon, 2024).

Chapter IV adopts a mixed-methods approach; this study begins with qualitative interviews to identify key engagement factors, which then inform the design of a structured quantitative survey. The questionnaire, developed based on prior literature and validated measurement scales, assesses chatbot effectiveness in fostering brand trust, satisfaction, and long-term commitment. Findings reveal that AI chatbot features significantly enhance customer perceptions, with ease of use and usefulness in shaping positive attitudes and strengthening brand connections. The research further underscores the role of AI-driven personalization in delivering sustainable customer engagement by optimizing digital interactions, reducing resource-intensive human support, and promoting long-term brand loyalty. By integrating TAM with customer-brand relationship theories, this study contributes to AI and sustainability research by highlighting how intelligent chatbots can facilitate responsible business practices, enhance operational efficiency, and promote digital sustainability through automation and resource optimization. The findings provide strategic insights for businesses seeking to design AI-driven chatbot systems that improve customer experience and align with sustainable digital transformation efforts. This study was published in *Sustainability* (Xia & Shannon, 2025).

CHAPTER II
A BIBLIOMETRIC REVIEW OF ANALYZING THE INTELLECTUAL STRUCTURE OF THE KNOWLEDGE BASE ON AI CHATBOT APPLICATION FROM 2005–2022

Chapter 2 presents a bibliometric analysis aimed at systematically mapping the intellectual landscape of AI chatbot research. As AI chatbots become increasingly central to digital service strategies across industries, the volume of academic literature surrounding their development, application, and user impact has grown substantially. To navigate this expanding body of knowledge and ensure a theory-driven approach to model development, it is essential to identify the key authors, foundational documents, and conceptual domains shaping the field.

The bibliometric review serves two primary objectives. First, it enables the identification of the most influential scholars, journals, and research clusters in the AI chatbot domain through citation and co-citation analysis. This helps to establish a robust understanding of the core themes and scholarly trends in the literature. Second, and more importantly for this study, the review provides a theoretical foundation for developing the conceptual framework in Chapter 3. By analyzing high-impact documents and frequently cited theoretical models, this chapter supports the selection of relevant constructs—such as those drawn from the Technology Acceptance Model (TAM) and relationship marketing theory—which guide the empirical investigation that follows. Through this structured, data-driven review, the chapter ensures that the research model is grounded in existing academic discourse while also revealing potential gaps and opportunities for extending knowledge on AI chatbots as e-service agents.

2.1 Introduction

Many economic sectors have benefited from Artificial Intelligence (AI) innovations, often known as machine intelligence (Kietzmann & Pitt, 2020). Increasingly, companies use Artificial Intelligence (AI) to alter their brands to decrease costs, boost efficiency, raise revenue, and enhance the customer experience (Adam, Wessel, & Benlian, 2021). Experts predict that by 2030, artificial intelligence might add $15.7 trillion to the global economy (Adam et al., 2021). From $1.3 billion in 2010 to $40. 4 billion in 2018, with over 3000 enterprises receiving over $400,000 in funding, significant investments in AI startups have increased dramatically worldwide. Investing in artificial intelligence is predicted to increase by as much as three times by 2024 (Kietzmann & Pitt, 2020).

During the COVID-19 epidemic, when people were confined to their homes and human agents were few, AI chatbots overgrew. Consumers today rely heavily on digital resources like AI chatbots to research items, decide which ones to buy, and ultimately choose which brands to buy (Adam et al., 2021). By 2026, the chatbot industry is predicted to be worth $10.5 billion. From 2019 to 2026, the customer service sector of the AI chatbot market is expected to expand by 31.6% (Adam et al., 2021). The bibliometric review approach, which aims to collect and evaluate all relevant literature on a topic, has not been used in previous reviews (Zupic & Čater, 2015). This bibliographic study aims to compile data about artificial intelligence chatbot services and analyze the conceptual theories. The study aims to accomplish the following questions through its research:

1. How many AI chatbot services are there, how quickly are they growing, and where are they most prevalent?

2. Which journal has contributed the most citations based on the AI chatbot?

3. Which cited and co-cited authors have contributed most to the literature on AI chatbot applications?

4. What is the “intellectual framework” of the AI chatbot service literature?

This research used an extensive bibliometric analysis of the literature on artificial intelligence chatbots. The analytical method examined bibliographic data from 571 chatbot service evaluation publications. This study employed quantitative bibliometric methods, including productivity, citation, co-citation, and scientific mapping (Zupic & Čater, 2015; Van Eck & Waltman, 2018). As was said earlier, this topic is new in studying AI conversational services. This analysis examined more 2005-2022 documents. So, this study examines the growing volume of AI chatbot service knowledge using bibliometrics.

2.2 Literature review

2.2.1 Definition of Chatbot

Chatbots are computer programs that mimic human communication by using Artificial Intelligence (AI) and Natural Language Processing (NLP) to comprehend requests from customers and provide automated replies (Adamopoulou & Moussiades, 2022a). Without human involvement, chatbots may help consumers quickly locate the answers to their inquiries using text or audio input (Shawar & Atwell, 2007). These days, customers can find chatbot technology in various settings, from smart home speakers to enterprise messaging platforms. The newest generation of AI chatbots is frequently referred to as "virtual agents" or "virtual assistants" (Chaves & Gerosa, 2021). Siri, Google Now, and Amazon Alexa take voice commands, and customers can even text them. For example, Zhou, Gao, Li, and Shum (2020) found that customers may ask the chatbot conversational questions about their needs, and it responds with information and further questions to narrow their search. Formerly, chatbots were text-based and could only respond to a small range of predefined questions with replies created by the chatbot's creators. Like an interactive FAQ (frequently asked questions), they were adequate only for the queries and answers with which they had been programmed, and they proved incapable of handling anything more sophisticated or unexpected (Ranoliya, Raghuwanshi, & Singh, 2017).

Chatbots have evolved to incorporate additional rules and natural language processing, allowing for a more conversational experience for the end user (Ghose & Barua, 2013). To be more precise, modern chatbots understand their surroundings and improve their language skills as they interact with more and more people. Modern AI chatbots employ NLU (natural language understanding) to comprehend the user's wants (Ait-Mlouk & Jiang, 2020). The next step is to employ cutting-edge AI capabilities to determine what the user is attempting to do. These systems depend on machine learning and Deep Learning (DL), both forms of AI with their subtleties, to build a database of questions and answers based on user interactions that become more specific over time (Braun, Mendez, Matthes, & Langen, 2017). This enhances their capacity to anticipate and meet the requirements of their users.

Furthermore, some modern chatbots employ sophisticated algorithms to deliver exceptional replies. Consumers are using AI chatbots for anything from interacting with smartphone apps to operating specialized products like intelligent thermostats and kitchen appliances (Xu et al., 2017). The uses in the corporate world are as diverse. Marketers use artificial intelligence chatbots to tailor client experiences (Bariş, 2020), IT departments to facilitate computer science to stimulate human conversation (Um, Kim, & Chung, 2020), and customer healthcare service departments to expedite incoming messages and point customers in the right direction (Oh et al., 2017).

2.2.2 History of Chatbot

Although chatbots have been for some time, it is only in the past few years that they have seen widespread adoption by both consumers and enterprises. ELIZA was the first chatbot (Weizenbaum, 1966), and other well-known chatbots were created in the latter part of the twentieth century (Adamopoulou & Moussiades, 2020b). For example, the WeChat bot creates a social network and facilitates the development of elementary-level conversational programs. It has become a model for how businesses and marketers may save costs without sacrificing the quality of online customer interactions. Although WeChat is less powerful and has several drawbacks compared to popular messaging platforms like Facebook Messenger, Slack, and Telegram today, customers can still build a brilliant bot on the platform (Zumstein & Hundertmark, 2017).

The first wave of artificial data technologies used to create chatbots debuted early in 2016. With the help of Facebook and other social media platforms, programmers may create a chatbot for a company's brand or service, allowing users to do various tasks within the messaging app (Kull, Romero, & Monahan, 2021). Now that chatbots are commonplace, users live in the conversational interface era.

2.2.3 Economics of Chatbot

AI chatbots' deep learning capabilities make interactions more precise over time, weaving together a web of appropriately worded replies as they engage with people. An AI chatbot's replies improve the longer it has been in use. As a result, an AI chatbot trained using deep learning may be better able to respond to a question and the underlying purpose of the question than one trained with more recently merged algorithm-based knowledge (Smutny & Schreiberova, 2020). With algorithm-based knowledge, chatbots create value for organizations and customers using modern AI chatbots (Nguyen et al., 2021).

Before the advent of fully developed e-commerce, customers who wanted answers to their inquiries, concerns, or complaints had to send an email or give the company a call. Nonetheless, it is a continual and expensive effort for many companies to staff customer service departments to meet unforeseen demands and retrain workers to respond consistently to identical or recurrent requests at all hours of the day or night. Chatbots may now manage consumer contacts 24/7, all while reducing expenses and increasing response quality (Smutny & Schreiberova, 2020). By taking over mundane chores, chatbots streamline processes and increase productivity. With its instant availability to an unlimited number of users simultaneously, a chatbot may also do away with the need for customers to wait for customer service over the phone or through other channels like email, chat, or the web. Customers are more likely to be loyal to a brand if they had a positive experience (Trivedi, 2019).

The cost of maintaining a 24-hour customer service center is high. It may also be impossible for other divisions, such as human resources. Outsourcing this task has spawned a whole industry but comes at a high price. Also, it lessens a company's ability to direct how its brand communicates with its target audience. Nevertheless, a chatbot is available anytime and assists the firms in defense during peak times (Lasek & Jessa, 2013). Using a chatbot can at least lessen the number of customers who need to speak with an actual person, saving money by keeping firms from hiring more people to deal with the growing demand.

Using chatbots may benefit lead generation and conversion rates in sales (Meyer-Waarden et al., 2020). For instance, a consumer looking through a website for a product or service can inquire about the various options and how they work. A chatbot can answer these questions and guide the customers toward a more informed buying decision (Khoa, 2021). Moreover, the chatbot may qualify the lead before connecting the buyer with a qualified sales representative for more sophisticated purchases through a multistep sales funnel. Choosing a chatbot platform may be simple, and the benefits to businesses and customers can be substantial. Companies may save money while still satisfying customers' need for instantaneous service using a conversational channel (Abdulquadri, Mogaji, Kieu, & Nguyen, 2021).

An online store might use a chatbot to tell customers more about what they are looking at, differentiate between similar models, and supply supplementary resources like how-to videos and user guides (Nichifor, Trifan, & Nechifor, 2021). Similarly, an enterprise company's human resources department may approach a developer needing a chatbot to provide employees with round-the-clock, self-service access to benefit information and ease of navigation.

2.3 Methodology

This section introduces bibliometric analysis performed to analyze related papers with AI chatbot service. The identified process of the source is from the scientific database of Scopus.

2.3.1 Identification of the Source

Many authors study the review and prefer to lay it out in the PRISMA (Preferred Reporting Items for Systematic Reviews and Analyses) (Figure 2.1). PRISMA can provide details such as search terms and exclusion criteria in the screening procedures (Moher, Liberati, Tetzlaff, & Altman, 2009).

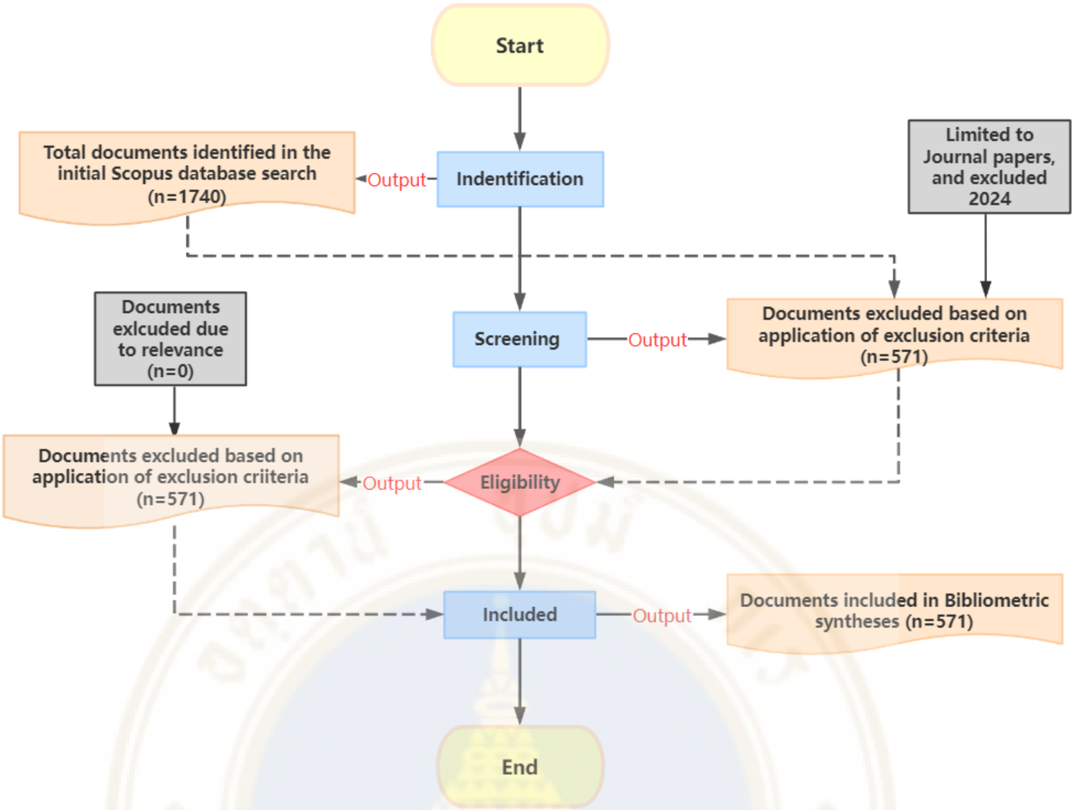

Figure 2.1 Identification of Sources with Prisma Flowchart

Scopus is a digital database widely used for bibliometric assessments (Zupic & Čater, 2015). Scopus can cover many areas (Griffith, Small, Stonehill, & Dey, 1974). This study focuses on artificial intelligence chatbot reviews, which rely on its database. With the chatbot services in locating historical sources, this advantage makes it a fantastic resource for interdisciplinary social science research (Falagas, Pitsouni, Malietzis, & Pappas, 2008; Mongeon & Paul-Hus, 2016).

First, several variations of AI and AI-related search terms (e.g., AI OR artificial intelligence) were utilized to find reviews of the chatbot service (e.g., consumer chatbot service OR customer chatbot service). This search technique is effective since it retrieves papers from academics actively developing and publishing AI chatbot services (Garfield, 2004). However, this search approach may also be limited, but it can be relevant to "artificial intelligence" (e.g., medical in AI, AI in computer science, chatbot service) (Van Eck & Waltman, 2010). Besides, it is essential to remember that the keyword searches used for the preliminary review included not just author-defined keywords but also text from titles and abstracts of publications indexed by Scopus (Krening & Feigh, 2018). So, there were numerous opportunities to locate "AI chatbot service" perspective articles in the literature on artificial intelligence.

Second, documents used Scopus filters and were manually inspected based on predetermined criteria for rejection (Zupic & Čater, 2015). In this way, researchers constructed a "Scopus list" of relevant papers about AIC chatbot services (Van Eck, Waltman, Dekker, & Van den Berg, 2010). Bibliographic information associated with the Scopus list was downloaded as an Excel spreadsheet (Hummonb & Doreian, 1989). That is why all the best evaluations on AI for chatbots have assembled their datasets, which researchers can find in Scopus.

Lastly, the researchers created a single Excel document that included all AIC review databases. There were 571 rows of bibliographic information from Scopus in the main spreadsheet (columns). Data includes author names, document titles, authors' affiliations, abstracts, funding information, citation data, and co-citation data (Liang, Lee, & Workman, 2020). As was previously noted, the "findings" were discussed in numerous studies published by the AIC. The reviews were subjected to bibliometric analysis, which included citation and co-citation analyses (Garfield, Pudovkin, & Istomin, 2003).

2.3.2 Data Analysis

The bibliographic data needed to be examined and rectified for "consistency" in the expression of author names before any data analysis could begin (Van Eck & Waltman, 2010). One example is Weston Jones, whose name appears both as "Weston, J." and "Weston, J. L." in several sources. A “thesaurus file” was made to handle the “disambiguation” of author names. During data analysis, the thesaurus file directs VOSviewer analytical software to substitute a generic term for each possible variation of a given name (Van Eck & Waltman, 2010). Finding solutions to the research questions that steered this evaluation necessitated an analysis of authorship trends (Small, 1997). The entire database was used in all analyses (i.e., the master spreadsheet).

With the help of VOSviewer 1.6.8, science mapping, we could see connections between papers on AI chatbot services written by different authors (Zupic & Čater, 2015). It has been shown that the "productivity analysis" aimed to identify the most related AIC researchers. The full dataset was analyzed in this study using VOSviewer and Excel (Van Eck & Waltman, 2011). VOSviewer's "citation analysis" was used to determine how often each author of the 571 papers comprising the review database was cited in other Scopus articles (Small & Griffith, 1974). In this research, this indicator is known as the number of "Scopus citations."

This is because there are variations in the depth of the documentation. Scopus is more often used in data analysis than Web of Science in citation output while less than Google Scholar (Merton, 1973). In this study, the researchers study three aspects: productivity analysis, co-citation, and intellectual framework. This is because high-impact authors, journals, and publications are believed to significantly affect the development of research and study fields (Price, 1965). Therefore, the Scopus citation analysis was augmented by a co-citation analysis performed in VOSviewer 1.6.8. (Zupic & Čater, 2015).

In order to maintain a comprehensive record of author relationships, the VOSviewer program additionally keeps track of the "citing authors" (Small, 1973). By looking at the “authors cited in the review database,” co-citation analysis can pinpoint relevant authors. Researchers often utilize co-citation analysis to find "connections" between prominent researchers in the same field (Small, 1997). For example, if a co-citation study shows that Weizenbaum and Atwell are “often co-cited” (e.g., 25 times), we can infer that their works are conceptually compatible (Zupic & Čater, 2015; Price, 1965; White & McCain, 1998).

Using co-citation matrices derived from cited authors, VOSviewer performs author co-citation analysis (ACA), producing a "science map" of the literature (Price, 1965). This analysis of AI chatbot services utilized an ACA map to demonstrate author overlap graphically (Skupin, Biberstine, & Börner, 2013). When taken as a whole, these findings illuminated the scholarly traditions or "intellectual framework" underlying the literature (Zupic & Čater, 2015; Price, 1965).

2.4 Results

In this section, the researchers discuss and answer the four research questions. Production growth and distribution have been analyzed to answer the first research question. Then, the researchers found the most cited journal based on Scopus. Moreover, cited and co-cited authors are discussed to answer the third question. The researchers also developed an intellectual framework to explain the AI chatbot service literature.

2.4.1 Analytical Characterization

Adam et al. (2021) forecast that the artificial intelligence chatbot progresses significantly in the following years. Indeed, many articles have appeared in print during the previous few years. Figure 2.2 presents the total number of documents that have grown dramatically in distribution from 2005 to 2022. Primarily, the papers in 2022 have been published almost twice compared to 2021.

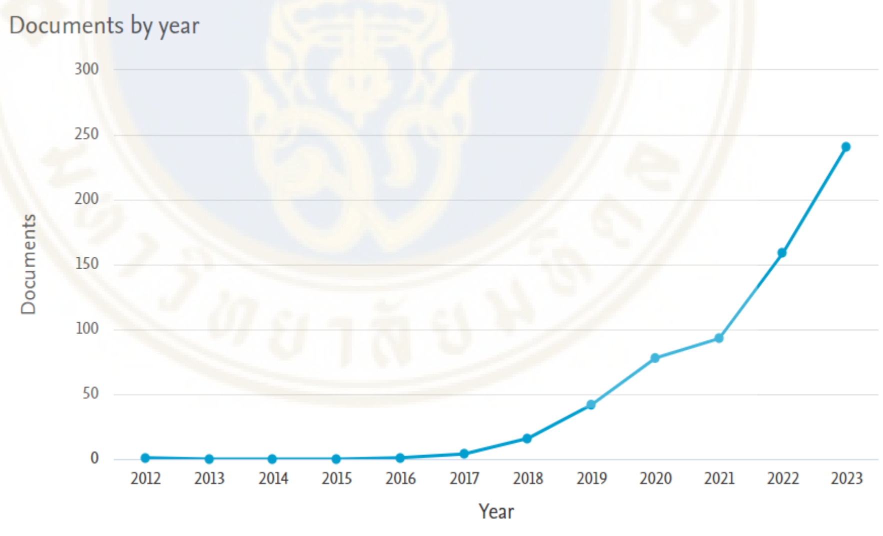

Figure 2.2 The Increasing Documents of AI Chatbots, 2005 to 2022 (n=571)

Besides, AI chatbots have recently become a new trend topic, and knowing the subject domains is worthwhile. The bibliometric review can provide clear and detailed information for disciplinary knowledge, so the researchers extract the data model from Scopus. Figure 2.3 introduces the most important study of documents by subject area. Computer science, engineering, social sciences business, management, and accounting researchers have comprised 61.7% of the literature. This hints at opportunities for substantial new developments to emerge from theoretical viewpoints and approaches from other fields.

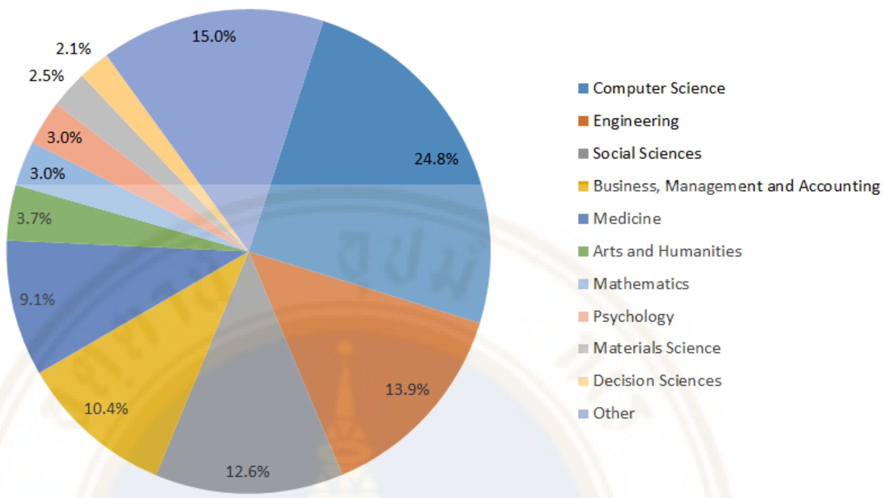

Figure 2.3 The Most Important Study of Documents by Subject Area, 2005 to 2022 (n=571)

(**Note**: The subjects are less than 2% combined in another group.)

Figure 2.4 is a world map illustrating AI chatbot literature's worldwide influence and concentration. The result is based on its roots in a particular country or area. The United States has the most published papers worldwide, which takes up 119. Then, India, South Korea, the United Kingdom, and China follow closely. Broadly, North America and Asia have contributed the most papers. Indeed, the papers from North America and Asia have taken up more than 60 percent based on the database from Scopus.

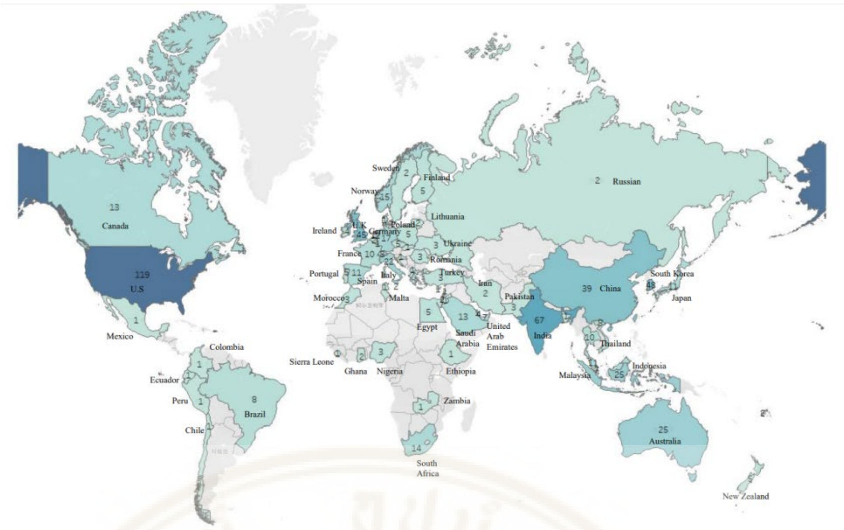

Figure 2.4 Geographical Distribution of Chatbot Service Papers across the World

2.4.2 Citation Analysis of Journal Impact

Trapp (2020) mentioned that journal impact from Scopus can help researchers quickly find a suitable journal. Indeed, Scopus' database can provide a reliable source for scholars to consider when finding a suitable journal to publish (Table 2.1). The most cited journal on AI chatbots is Computer in Human Behavior. The other highly cited journals are Journal of Business Research, Digital Health, and Electronic Markets. The academic publication Computers in Human Behavior takes a psychological approach to study how people interact with computers. The AI chatbot is one of the suitable topics to discuss human-robot interaction. That is why many researchers submitted their papers in Computers in Human Behavior. Besides, with the economic development, many firms use the chatbot as their representative to connect with their customers. Business studying in AI chatbots has increased a lot in recent years. Journal of Business Research has been ranked in second place. It is a proper journal to publish the relationship between the customers and companies. Moreover, the Journal of Business Research investigates a broad spectrum of decision-making environments, processes, and activities to provide insights with application in theory, practice, and society.

Furthermore, hospitals have also built their digital platform to help patients. As one of the most influential journals, Digital Health is suitable for a scholar who wants to publish advanced technology in the health industry, such as an AI chatbot application. Here are the most influential ranking journals.

Table 2.1 The Top Cited Journal of an AI Chatbot, 2005 to 2022

Rank	Source	Documents	Citation
1	*Computers in Human Behavior*	10	801
2	*Journal of Business Research*	10	405
3	*Digital Health*	4	170
4	*Electronic Markets*	4	168
5	*IEEE Access*	8	132
6	*Journal of Medical Internet Research*	12	127
7	*International Journal of Bank Marketing*	4	119
8	*Journal of Retailing and Consumer Services*	4	102
9	*Sustainability* (Switzerland)	5	95
10	*Journal of Service Management*	5	91
11	*Applied Sciences* (Switzerland)	15	47
12	*Information Systems Frontiers*	6	44
13	*Electronic Commerce Research and Applications*	4	33
14	*Proceedings of the ACM on Human-computer Interaction*	4	32
15	*Telkomnika (Telecommunication Computing Electronics and Control)*	4	30

2.4.3 Scopus Citation and Co-citation Analysis of Author Impact

To answer research question 3, the researchers have analyzed the author's citation and co-citation, respectively. Small (1997) claims that bibliometric research can reveal which academics have contributed significantly to the body of knowledge. Scholars may be identified by their fields of study, countries of origin, and several publications via citation and co-citation studies. Finally, the quantity of citations is used to rank the academics (Table 2.2). The table shows the top 15 cited authors in the AI chatbot area from 2005 to 2022.

Table 2.2 Top Cited Author of AI Chatbot, 2005 to 2022

Rank	Author	Nation	Focus	Number of documents	Scopus citation
1	Araujo, T.	U.S.	Computer science	3	373
2	Nadarzynski, T.	U.K.	Digital health	3	164
3	Yu, S.	The U.S.	Customer service	3	146
4	Følstad, A.	Norway	Computer science	5	93
5	Cheng, Y.	China	Customer service	4	78
5	Jiang, H.	China	Customer service	4	78
7	Jin, S. V.	The U.S.	Customer service	3	53

Rank	Author	Nation	Focus	Number of documents	Scopus citation
7	Wang, X.	Australia	Customer service	3	53
7	Youn, S.	The U.S.	Customer service	3	53
10	Yang, H.	South Korea	Computer science	4	40
11	Zhang, Z.	China	Digital health	3	30
12	Shin, D.	South Korea	Computer science	4	27
13	Cheng, X.	China	Customer service	3	24
14	Mou, J.	China	Customer service	4	23
15	Lee, S.	The U.S.	Computer science	3	21

The top 5 cited authors of AI chatbots are Araujo, Nadarzynski, Yu, Følstad, and Cheng. Araujo is from the U.S. and is the most cited author. He focuses on human-robot interaction and deep learning in AI. Araujo, Helberger, Kruikemeier, and De Vreese (2020) draw on computer science theories and the growing research on algorithmic appreciation and perceptions to investigate the relationship between individual characteristics and attitudes toward AI-automated decision-making. They concluded that customers worry about the risk of AI chatbot applications and have a neutral attitude toward the usefulness and fairness of AI chatbot applications. Nadarzynski, Miles, Cowie, and Ridge (2019) found that most people online would be open to interacting with a health chatbot, while skepticism about the technology likely reduces users' willingness. To maximize adoption and utilization, AI-powered health chatbot intervention designers should use a user-centered, theory-based approach to ease patients' fears and improve their experience. In addition, Cheng and Jiang (2020) studied the customer-brand relationship with the AI chatbot application. They extended the TAM model and found that based on the AI users' experience, the customer-brand relationship has mediated with communication quality and customer response.

This section employed Author Co-citation Analysis (ACA) to identify the more extensive group of influential academics (Table 3). Co-citation analysis pinpoints influential academics who have affected authors (Acedo, Barroso, Casanueva, & Galan, 2006). The results in Table 3 are notable in a few ways. A co-citation analysis uncovered several academics whose AI chatbot scholars often cite theoretical and methodological publications but have not published them on artificial intelligence for chatbot services.

Table 2.3 Top Co-cited Author of AI Chatbot, 2005 to 2022

Rank	Author	School of thoughts	Co-citations	Total link strength
1	Følstad, A.	Computer science	139	6952
2	Nass, C.	Computer science	133	6720
3	Sundar, S. S.	Computer science	129	6377
4	Dwivedi, Y. K.	Digital health	108	7261
5	Venkatesh, V.	Computer science	95	6039
6	Araujo, T.	Computer science	94	5207
7	Benbasat, I.	Customer service	89	4727
7	Ko, E.	Computer science	89	4903
9	Davis, F.D.	Customer service	88	5704
9	Grewal, D.	Digital health	88	3551
11	Brandtzaeg, P. B.	Computer science	81	4380
12	Moon, Y.	Computer science	80	4418
13	Hair, J. F.	Customer service	79	3597
13	Kim, S.	Customer service	79	1282
15	Atwell, E.	Customer service	74	2876

Table 2.3 also stands out for the sheer size of its co-citation sums. As an illustration, three authors, Følstad, Nass, and Sundar, have been cited over a hundred times. Flstad's documents were cited in 24.3% of the 571 documents in the AI chatbot, with 139 co-citations. After Nass, the next best author is Sundar. However, this examination of co-citations shows that the most vital links are not necessarily among the top three co-citations. Dwivedi's "total link strength" is greater than any other scholar's, demonstrating his outsized influence in this study (Table 3). We found that the total link strength of the top 15 authors is above 1,000. However, some authors may have the most co-citations, yet their links may not be as strong as others.

In addition, this statistic tells us that the author Følstad has been widely cited in the Scopus-indexed field of AI chatbots (i.e., total co-citations). Nonetheless, he does not share many citations with other authors in his works (i.e., total link strength). However, Dwivedi has a total link strength of 7,261 thanks to the prevalence with which other researchers mention his many published works.

Furthermore, the author's research into other disciplines provides another practical angle on their influence (Waltman & Van Eck, 2012). Many authors are deeply interested in customer services and the computer science behind AI chatbot applications. However, few authors have explored even a fraction of digital health. The mentioned author mainly focuses on marketing services, computer science, and digital health in his or her research. Analysis of author co-citations is particularly well-suited to elucidating the interconnectedness of different fields (Waltman, Van Eck, & Noyons, 2020).

2.4.4 Intellectual Structure of the AI-related Knowledge Base for the Chatbot Service

The study's final question aimed to tease the "intellectual structure" of the AI chatbot-based knowledge. For this study, we built a co-citation map to illustrate the connections between the 92 researchers who each earned at least 30 citations in the reviewed articles' reference lists (Table 3). The relative co-citation frequency of an author is represented by the size of a "node" on a co-citation map. The closeness of nodes represents the frequency with which two authors have "co-cited" one another. Among academics, "links" represent the frequency with which other academics have cited both authors. Finally, VOSviewer groups researchers into "schools of thought," which reflect the knowledge base's underlying intellectual structure (Zupic & Čater, 2015; Waltman & Van Eck, 2012, 2013).

Computer science, digital health, and marketing service are the three main intellectual structures in the literature on artificial intelligence for robot service. It is essential to realize that there are many connections between the three AI for chatbot service schools. Author productivity and citation analyses have already suggested that artificial intelligence is the central topic of study for chatbot service research (Waltman et al., 2010). These connections were mapped using co-citations with a "self-organized" structure (Waltman & Van Eck, 2013).

There are three leading schools of thinking on this topic, the largest of which is held by researchers in the field of computers. This theoretical map is centered on computer science (e.g., Nass, Dwivedi, Venkatesh, and Araujo). As we previously said, several concepts from the field of computer science have found their way into AI. In addition, the digital health field of the co-citation network highlighted smaller "clusters," including Dwivedi and Grewal. There are a total of 31 items here that pertain to studies in the area of digital health. Authors concerned with customer service make up the third school of thought. This group of authors includes Atwell, Liu, Chen, Lee, Zhang, Zhou, and Li, all prominent in their respective fields of AI chatbot application service (Figure 2.5).

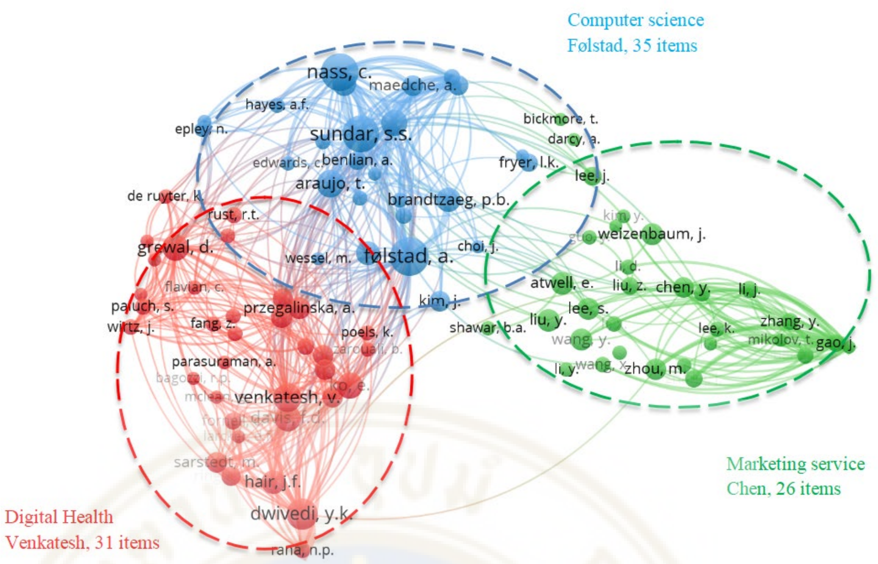

Figure 2.5 Author Co-citation Map Showing the Schools of Thought on Artificial Intelligence for Chatbot Service
(Citation threshold 30; display 92 authors)

2.5 Discussion

This bibliometric examination aims to identify "self-organized" patterns of knowledge production that develop through time across different fields of study (Zupic & Čater, 2015). This inductive approach aimed to understand the conceptual development of AI for chatbot services. The report looked at the interest in artificial intelligence research in various fields. We can find the related papers extracted in the Scopus database. The most significant document database ever created has benefited several fields, including computer science, digital health, decision science, business, management, and accounting. However, this criterion proved insufficient to resolve this matter due to variations in document identification standards. Hence, we used productivity, citation, and co-citation analysis to learn more about the issue.

Firstly, according to productivity analysis, we could conclude that since 2017, the paper related to AI chatbots has sharply increased, and in the future, they will continue to grow. Computer science has also undertaken the most significant programmatic research. Indeed, many researchers want to know how intelligent technology (e.g., deep learning, machine learning) is behind the chatbot. Moreover, we also found that authors from the United States have published more papers (119) than other Asian countries, such as China, Japan, and India.

Secondly, we used the citation to rank the journals to find which one the authors wanted to contribute to. We found the top 15 journals from the Scopus database. Those journals are reliable sources for researchers wanting to publish a related AI chatbot paper. Besides, the citation analysis also supported the most influential authors, showing that the American author (Araujo) has the most citations. In addition, computer science has had a much more significant impact on artificial intelligence scholarship through citations than scholars in any other discipline.

Thirdly, the author's co-citation analysis offered a graphical depiction of these tendencies. The most frequently referenced authors now receive more than 100 citations. Nevertheless, these schools featured tightly knit communities of scholars, many of whom were frequently mentioned. This proved that there is a sizable "global community of AIC scholars" interested in solving chatbot service issues with AI.

Fourthly, chatbot services have been AI's primary area of growth over the past decade. AI has been integrated as a central construct in this discipline, as evidenced by the vital citation and co-citation effect among academics. On the other hand, AI seems to be ahead in several ways. It has also been suggested that reviews of science maps can be used to identify "related scholars" or authors who have had a lasting impact on the conversation within a given field of study (Kumar & Reinartz, 2018). Author co-citation analysis, mainly the co-citation map stated above, highlighted the ideas, concepts, and techniques established in artificial intelligence for chatbot services. Chatbot services utilizing AI to respond to customer inquiries are becoming increasingly popular.

Lastly, "AI chatbot application"-related authors had a weak citation impact. To be sure, "co-citation analysis" is the only reason fewer articles focus on AIC research. Evidence of this effect may be seen in the co-citation map, which shows relationships between strategy researchers and those in other fields.

2.6 Conclusion

This literature study contributes novelly by providing empirical evidence for the philosophical framework of inquiry into "artificial intelligence for chatbot support." The lack of research into AI for chatbot services is unfortunate and can be attributed to the popularity of more niche themes. In addition, the bibliometrics review on AI for chatbot support can only look at one database. Thus, new datasets are required for the bibliometrics review, which analyses the applications of AIC and their outcomes in other fields. As previously mentioned, most AI research is done in computer science, with certain exceptions in marketing. The author hopes that by conducting this analysis, academics will have a clearer picture of the AIC landscape and better pinpoint the authors most relevant to their specific areas of study. According to the author's co-citation map, this is already happening based on patterns in the cited body of work. We expect a similar map to be generated in 10 years to show the expansion and enhanced differentiation of current schools of thought and the increasing density of links between them.

2.7 Limitations

This bibliometric analysis aimed to assess researchers' dedication to studying chatbot services, single out leading lights in the field, and shine a light on fundamental ideas in artificial intelligence. In this section, we go over the limits of the review, explain how we interpreted the results, and then highlight numerous implications.

Firstly, when compared to more conventional methods of analysis (Arkorful et al., 2020), bibliometrics is limited in its ability to provide light on fundamental concerns such as "whether," "how," and "why" specific methods get better results than others. One bibliometric review's strength is its capacity to summarise overarching trends in a topic and assess the structural aspects of knowledge production (Morgan, 2017). Therefore, it is crucial to emphasize that this goal of the analysis was restricted to revealing knowledge generation patterns and theoretical trends in artificial intelligence research on chatbot services.

Secondly, the scope of this review was limited, as it would be with any analysis, by the amount of time available to meet the criteria for data analysis. In light of this, the author concedes that the conclusions do not cover the scope of relevant domains despite the breadth of artificial intelligence addressed in this research. The datasets only covered a limited time because AI for chatbot services is a relatively new field. There are not many papers to review. More work needs to be done in the future to collect data to get a better grasp of "artificial intelligence for chatbot service." As we have already established, using a search strategy is based on a broad term (i.e., artificial intelligence). Several AI-related documents for chatbot services may have been missed because they were not filed under that heading.

Lastly, this evaluation uses a bibliometric approach to look at frequent occurrences in the literature (e.g., highly cited authors). This is based on the belief that locating influential research might help bring attention to important concepts. However, it is possible to miss both emerging trends that have not yet received many citations (Huang & Rust, 2018) and competing viewpoints that have not yet won over most of the community.

CHAPTER III
CONCEPTUALIZING AI-CHATBOT APPLICATION AS AN E-SERVICE AGENT TO DEVELOP A CUSTOMER-BRAND RELATIONSHIP

This chapter aims to develop the conceptual framework and formulate the research hypotheses guiding this study. E-service agents conceptualize chatbots not merely as technical tools but as autonomous service representatives that play a role in delivering brand experience and shaping consumer perceptions. This framing is especially relevant in digital service contexts where human–AI interaction substitutes for traditional interpersonal service delivery. TAM is utilized to assess how users form cognitive appraisals—specifically, perceived ease of use and perceived usefulness—based on their interaction with chatbot design features (e.g., interaction quality, customization). The A-B-C model complements TAM by providing a structure for understanding how these appraisals translate into affective responses (attitude) and ultimately behavioral tendencies related to brand relationships, such as trust, satisfaction, and commitment. Thus, these conceptualizations offer a robust framework for understanding not just whether users accept chatbots, but how and why chatbot design impacts customer–brand relationships, particularly in AI-driven service environments.

3.1 Introduction

In the current competitive environment, chatbots have become an important part of online shopping by promptly responding to customers and guiding users through purchasing (Luo et al., 2022). This can increase the customer experience and the companies' sales, focusing more on brands (Lee, 2023). Furthermore, chatbots could gather valuable customer preferences and behavior data, enabling companies to optimize their marketing strategies and product offerings for better performance in the competitive online marketplace (King, 2023). With this significance, artificial intelligence (AI) chatbot has completely changed how companies communicate with their customers online (Lee et al., 2023). During their initial versions, first-generation chatbots provided simple, preprogrammed responses, frequently annoying users due to their restricted functionality. AI chatbots have fundamentally changed customers' interactions with brands (King, 2023). Modern chatbots use machine learning algorithms to comprehend natural language, pick up on interactional cues, and respond with more appropriate responses for the given context (Kietzmann & Pitt, 2020). They can respond to intricate questions, provide product recommendations, and even act out dialogues that resemble a human's. Customers increasingly use internet tools like AI chatbots for information, shopping decisions, and brand selection (Dearing, 2021). Figure 3.1 shows how the AI chatbot has worked in the customer service area.

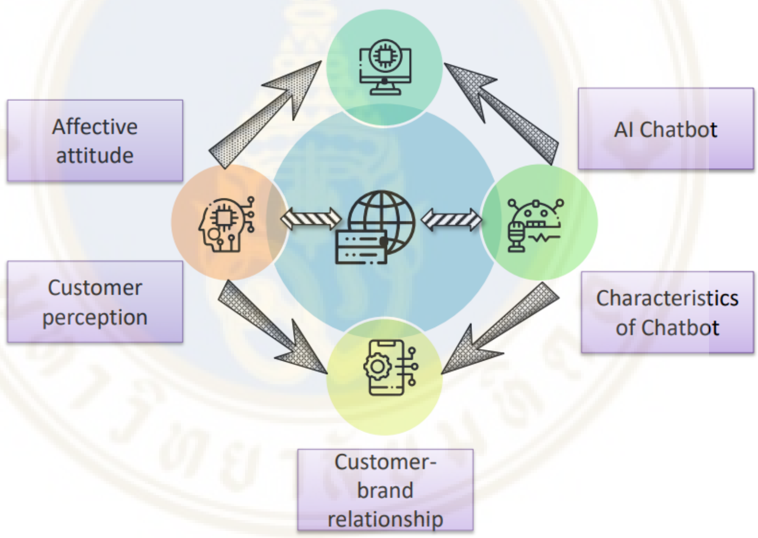

Figure 3.1 The AI chatbot working mode

Xia et al. (2023) studied bibliometric analysis in service marketing with chatbots and found only 571 pieces of work from 2005 to 2022. Although chatbots are a reasonably new concept, customers expect AI chatbots to respond quickly and accurately to their queries. Customers appreciate when AI chatbots can personalize their interactions based on past interactions or customer data. They want AI chatbots to be easy to use and navigate, remember their preferences, and provide tailored entertainment, recommendations, or solutions, increasing customer brand relationships

(Lee et al., 2023). Literature found that customers' positive attitudes toward the brands can increase the customer-brand relationship (Hwang et al., 2021). When the brands are presented genuinely and responsive to the customers, it could increase the customers' feeling of trust and satisfaction. This positive attitude through the lens of the Technology Acceptance Model (TAM), two key indicators, perceived ease of use and perceived usefulness, is vital in enhancing the positive attitude (Al-Gasawneh et al., 2022). Various studies found that TAM indicators can increase the customers' positive attitude, which could increase the brand relationship (Al-Gasawneh et al., 2022; Saparudin et al., 2020).

TAM factors, namely perceived ease of use and perceived usefulness (Davis, 1989). TAM model helps us understand important technology-related factors. However, as the technology spreads and becomes more widely adopted, new factors—like the brand of the technology—also become important and need to be considered. As Rogers and Cartano (1962) pointed out, the conditions around technology change over time during the diffusion process. Although TAM is not a brand preference model, TAM can still be used with a little adaptation. Early on some observers recognized a problem in that TAM originally aimed to explain early technology adoption. It may not be entirely appropriate to use TAM to examine “technologies that were already familiar to the individuals at the time of measurement” (Venkatesh et al., 2003). Our adaptation was to look at satisfaction (a brand issue) using TAM, rather than attitude toward the technology in standard TAM. These actions address customer needs and demonstrate a commitment to their well-being and satisfaction, strengthening the emotional connection between the customer and the brand (Huang, 2020). Proactive problem-solving initiatives by the brand can enhance perceived ease of use by streamlining processes, reducing complexities, and ensuring seamless customer interactions (Dahri et al., 2024). Similarly, personalized interaction and customization contribute to perceived usefulness, as customers perceive the brand's offerings as tailored to their specific needs and preferences, thereby adding tangible value to their experiences (Algahtany, 2023). Furthermore, integrating elements that evoke perceived enjoyment, such as gamification or interactive features, not only enhances user experience but also positively influences the brand's overall perception, reinforcing the customer-brand relationship (Dahri et al., 2024). By increasing attention to these aspects, brands could increase the favorable environment where not customer feel easy to find the brand but also enjoy it, which could lead to an increase in the attention of customers toward customer-brand relationship (Dahri et al., 2024; You et al., 2021) which increase the company's market shares in customers.

Therefore, this study focused on the adopted Technology Acceptance Model (TAM). In addition, individual attitudes concerning particular objects towards the customer-brand relationship are also important (Ajzen & Kruglanski, 2019). Thus, this study also incorporates customer attitude to explain why the chatbot can lead to a successful customer-brand relationship. According to the a-b-c model by Breckler et al. (1985), attitude is represented by three components: cognitive (think), affect (feel), and behaviors (do). Thus, this study proposes that the characteristics of the chatbots (as a focal object of interaction) shape customers' perception towards the chatbots, represented by perceived ease of use and perceived usefulness from TAM. They also influence how customers feel about the chatbots, represented by affective attitude, which leads to the customer-brand relationship as a behavioral intention towards the brand. Keeping in the previous discussion, this paper explores the application of AI chatbots as e-service agents and their critical role in developing customer-brand relationships. To achieve the overarching goal of this article—examining how a brand can develop a chatbot to enhance its customer-brand relationship—researchers have framed the research questions as below:

1) How can a chatbot facilitate the development of customer-brand relationships?
2) How do specific dimensions of the chatbot affect customers' perception of the use of the chatbot?
3) How do customers' perceptions of the chatbot induce their affective responses?
4) What is the role of customer attitude towards the chatbot in customer-brand relationship development?

The study contributed to the research objectives in different ways. At first, in the current study, researchers integrate the A-B-C model, which includes cognitive, affective, and behavioral components, providing a nuanced understanding of how various external factors influence customer perceptions to build customer-brand relationships. Specifically, interaction, perceived enjoyment, problem-solving, and customization are crucial in shaping affective attitudes, which drive customer-brand relationships. Second, extending TAM to the context of AI chatbots, researchers offer a robust framework for understanding how these technologies can be leveraged to enhance customer-brand relationships. Besides, this research also expands the knowledge of customer-brand relationships by assessing itself (commitment, brand trust, and satisfaction) antecedents (i.e., e-service agent market effort, TAM model, and attitude) in the AI chatbot. However, the existing literature still lacks a complete picture of the factors that may affect the current customer-brand relationship in the AI chatbot. Third, integrating TAM indicators such as perceived ease of use and perceived usefulness alongside factors like problem-solving, interaction, customization, and perceived enjoyment, this model provides a suitable mechanism through which brands could increase deeper connections with their customers, laying the foundation for future research and practical applications in brand management and consumer engagement strategies.

The study was divided into four chapters: a literature review covering theoretical and empirical literature reviews. Research methodology where covered the methods of data collection. Results and discussion were discussed in the next section and supported results with relevant findings. Implications were discussed at the study end, where theoretical and practice implications were discussed.

3.2 Literature review

3.2.1 Conceptual Model of AI chatbot

A brand is essential for marketing and business strategies, and establishing a strong brand is also the key to success for a business. According to Khamitov et al. (2019), employees are instrumental in developing the customer-brand relationship. However, the rise of the internet and social media has transformed customers' expectations for communication with each other and brands (Ghaniabadi, 2024). AI applications have provided businesses various marketing capabilities, including automating brand communication (Kumar et al., 2024). Customers perceive their interactions with AI chatbots as similar to those with service providers (Li & Shin, 2023), improving brand communication efforts and outcomes (Ghaniabadi, 2024). Hence, like human service agents, AI chatbots or e-service agents can facilitate the development of the customer-brand relationship.

As customer relationships through chatbots are an important perspective, it is generally accepted that the customer-brand relationship is a multi-dimensional construct. For instance, Cheng and Jiang (2022) view customer-brand relationships as a construct of commitment, self-connection, intimacy, and satisfaction. This conceptualization of customer-brand relationships has then been adopted by several recent studies (Kim et al., 2016). Thus, this research studies CBR as sub-dimensional constructs represented by three dimensions: 1) satisfaction, 2) trust, and 3) commitment. While constructs such as satisfaction, trust, and commitment are traditionally regarded as attitudinal or cognitive-affective states, this study positions them within the "behavioral stage" to reflect their role as proximal indicators of future behavior. According to Ajzen's (1991) Theory of Planned Behavior, intentions—formed from attitudes, subjective norms, and perceived behavioral control—are the immediate antecedents of actual behavior. In a similar vein, trust and commitment, as conceptualized by Morgan and Hunt (1994), are essential psychological states that drive future behavioral outcomes, such as brand loyalty, repurchase, and advocacy. Therefore, although not directly observable behaviors themselves, these constructs serve as strong predictors of customer engagement behavior. Ever since other studies have looked at what defines satisfaction, but it has consistently gone back to the initial definition, suggesting that how well performance and expectations are met is measured by satisfaction (Hole et al., 2018), who view brand trust as being reliable and honest. The concept of trust in AI is, indeed, not limited to the intention towards technology adoption but also to brand trust (Siau & Wang, 2018). Since AI chatbot is a new technology, customers may experience uncertainties. In general, satisfaction, brand trust, and commitment are worth studying in CBR as the constructs can explain the relationship between the brand and customers. Therefore, the researchers propose that customers' satisfaction, brand trust, and commitment towards the AI chatbot are key constructs that explain customers' relationship with the AI chatbot.

The positive attitude of the customer toward the brands could increase the customer-brand relationship. Displaying proper care and responsiveness to their customers increases the trust level and satisfaction (Choung et al., 2023). This positive attitude can be evident in various forms, such as proactive problem-solving, personalized interaction, tailored customization, and enjoyable experiences (Chocarro et al., 2023). These actions address customer needs and demonstrate a commitment to their well-being and satisfaction, strengthening the emotional connection between the customer and the brand (Chocarro et al., 2023). Therefore, this study demonstrates that when customers believe positively about the AI chatbot, they are more likely to evaluate the brand positively. This, in turn, leads to their intention to develop and/or maintain a relationship with the brand.

Moreover, through the Technology Acceptance Model (TAM) lens, two key indicators, perceived ease of use and perceived usefulness, are vital in enhancing the customer-brand relationship. The TAM model is most frequently utilized in research investigations (Venkatesh et al., 2003). TAM's primary goal is to predict how consumers will embrace new technologies and raise attention to information system problems before widespread adoption. The TAM is cantered on two key constructs: perceived usefulness and perceived ease of use. For AI chatbots, perceived usefulness (how beneficial users perceive the chatbot to be) and perceived ease of use (how easy it is for users to interact with it) are crucial factors influencing user acceptance. The original TAM focuses on these factors, aligning with AI chatbot adoption's central concerns. Therefore, the researchers adopted the original TAM model of perceived ease of use and perceived usefulness to form the foundation. Researchers have created several models (Davis, 1989; Venkatesh et al., 2003) over the last few decades to comprehend the characteristics of the technology. The efficacy of these models for numerous information technology-based applications has been repeatedly tested (Mun et al., 2006). The TAM model indicators are shown in Figure 3.2

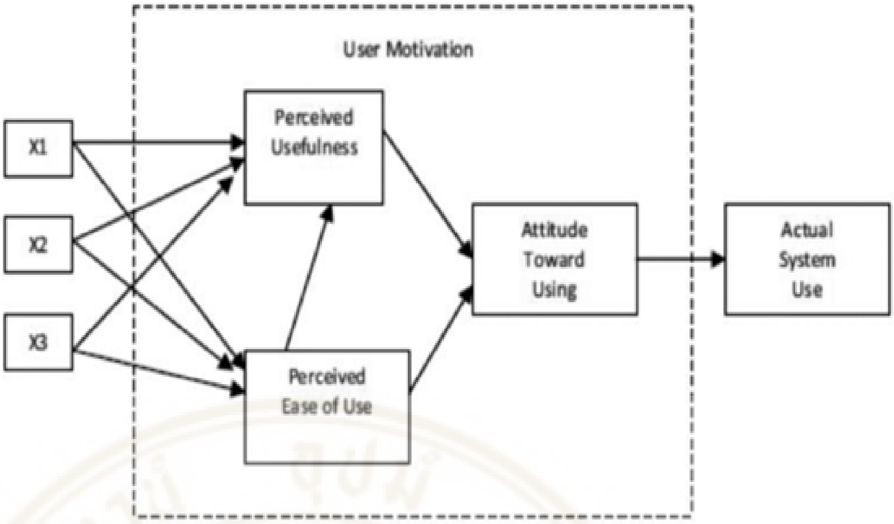

Figure 3.2 Original Technology Acceptance Model (Davis, 1989)

Based on the previous study and conceptual theories, the researchers expect to extend TAM models in the AI chatbot context by including service agent marketing effort as an external factor explaining how customers perceive the AI chatbot. Based on TAM frameworks, the study also hypothesizes that user's perception of the AI chatbot about its ease of use and usefulness facilitates the development of a customer-brand relationship through their attitude. Figure 3.3 depicts the constructs and the relationships under investigation in this study.

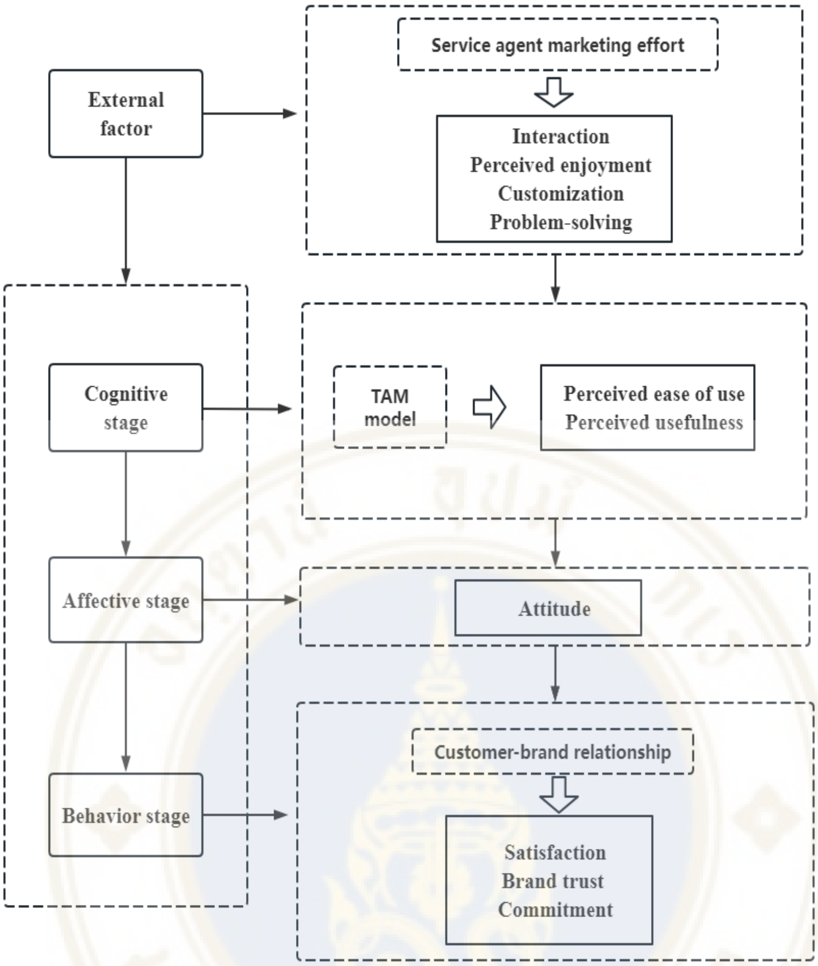

Figure 3.3 Conceptual Model of AI chatbot

3.2.2 Characteristics of AI chatbot influence on technology adoption

In the past, service agents relied on employees to help build customer relationships. In many companies, service agents address customers' issues and solve their customers' problems. Many causes have contributed to unprecedented challenges in the service sector, including intense worldwide rivalry, rapid technology change, and more mature client expectations (Reig et al., 2020). With the evolution of AI, many service organizations have integrated AI chatbots as part of their communication strategy to increase competitiveness, differentiation, and performance in the digital landscape. With AI chatbots, service organizations can provide essential marketing efforts, such as customization and influencing customer decisions (Gautam & Sharma, 2017). Various AI chatbot dimensions have been discussed in the extant literature.

Among those interactions, problem-solving perceived enjoyment, and customizations are important characteristics of AI chatbots, which are discussed in the next section.

3.2.2.1 Interaction with TAM model. Interaction is the first dimension, representing online contact between customers and AI chatbots via the internet. Currently, a chatbot has used up to one-third of online conversations; the amount of use is predicted to rise (Shumanov & Johnson, 2021). Compared with human service, Chung et al. (2018) have mentioned that chatbots can change the business industry through two-way communications. Reig et al. (2020) argued that AI chatbots using machine learning gain more competence throughout their customer interaction. Furthermore, past studies (Alassafi et al., 2022; Taufik & Hanafiah, 2019) have identified interaction as a key external factor influencing user perceptions of new technology. For example, Alassafi et al. (2022) discovered that when users perceive interactions as human-like, their perceptions of the ease of use and usefulness of e-learning systems can encourage continued usage. Indeed, they reasoned that good interaction between the students and the e-learning system can encourage continued usage. Similarly, customers seek interactions during their service consultation. When customers encounter a new technology, such as a self-check robot service, human-like interaction enhances their perception of its ease of use and usefulness (Taufik & Hanafiah, 2019), thus facilitating the adoption of the new technology. In addition, interactive and two-way communication between customers and computer-mediated communication, such as chatbots, leads customers to evaluate the technology's ease of use and usefulness positively (Lee et al., 2013). Furthermore, researchers have found that past studies by Ladhari et al. (2020) indicated that when customers perceive their interactions with e-service agents such as AI chatbots to be courtesy, responsive, knowledgeable, and close to those with a human agent, they enjoy the interactions and find their interactions helpful for their purchasing decision process.

3.2.2.2 Perceived enjoyment with TAM model. Perceived enjoyment is another key facet of the AI chatbot. The perceived enjoyment has been developing for many years. Perceived enjoyment, adapted from Davis et al. (1992) in the context of a website, refers to the extent to which using a computer is considered enjoyable, irrespective of any potential performance outcomes. In the AI chatbot context, customers engage with a chatbot for hedonic values, such as pleasure and enjoyment. Cheng and Jiang (2022) found enjoyment crucial in determining customer participation with a chatbot service. When entertained, customers interact with the AI chatbot to carry out the tasks they are looking for. Thus, if the companies can provide appropriate opportunities to assist their customers, the customers will increase enjoyment (Hsu et al., 2023). Pillai et al. (2020) have identified that the interaction between the chatbot and customers should be entertaining. In particular, since AI chatbots learn to simulate a human conversation due to their adjustability to the collected data, customers are likely to perceive their interaction with the chatbot, including the information obtained, as entertaining (Ramzan et al., 2023). Furthermore, perceived enjoyment has been considered a key factor in explaining customers' technology acceptance on the Internet in various settings (Abzari et al., 2014). Empirically, Abzari also suggested that perceived enjoyment also played an important role in quickly influencing the learning process, which can increase their interest in learning. Furthermore, the positive impact of perceived enjoyment on perceived ease of use has been observed in other contexts, such as mobile banking and social robots (Limakrisna & Moeins, 2024). Limakrisna and Moeins (2024), for example, found that a mobile banking interface can capture users' attention when using an online banking system that increases relationships with companies through improving attitudes. Thus, perceived enjoyment is crucial in a digital landscape.

3.2.2.3 Customization with TAM model. Another important dimension of AI chatbots is customization. Customization is defined as the process of adapting a product or service to meet the specific tastes or requirements of an individual or organization (Cheng & Jiang, 2022), and it has been studied in different fields. AI chatbots cater to each chat smoothly without requiring human supervision (Choung et al., 2023). Indeed, the best and most efficient customization the AI chatbots provide is the ability to recommend products that fit user preferences. Since customization positively affects customer satisfaction, Ding and Keh (2016), AI chatbots with the ability to customize to individual customer interaction can improve customer satisfaction with the brand. In other words, customization is another external factor explaining technology adoption in various contexts, such as mobile banking (Albashrawi, 2021). For example, customization has been found to substantially impact online retailers' perceived usefulness and ease of use (Bhatti & Bauirzhanovna, 2023).

Joshi et al. (2021) studied how advanced technology in retail customized young customers' perceived ease of use and usefulness in electronic retailing. Albashrawi (2021) also found in mobile banking that when customers perceive that the digital transaction system can be customized to fit their mobile banking behavior, they become familiar with the system. As a result, customers perceive the system to be easy to use (Wijaya et al. (2021) and find their experience using mobile banking helpful system (Lee et al., 2023). Therefore, customization is necessary to keep in AI chatbots.

3.2.2.4 Problem-solving with TAM model. Problem-solving is another critical dimension of AI chatbots. Problem-solving defines a problem and determines its primary cause, choosing potential solutions and putting them into action to help customers (van Aken & Berends, 2018). Likewise, AI chatbots can relieve the pressure of any organization with their ability to handle the basic questions and issues customers have independently. They can be created using AI to filter customers' inquiries and difficulties, allowing them to quickly offer a set of diagnostic questions to characterize the problem type. The problem-solving in technology adoption across various sectors can influence customers' perceived ease of use and usefulness. Empirically, Lin (2019) further found that problem-solving positively influences the perceived usefulness and ease of use within the innovative online learning application. Similarly, other authors found that AI chatbots become important indicators by providing too many solutions to influencing customer behavior (Sheth et al., 2019). This is because AI chatbots support a new layer function to solve customers' problems and influence their perception of the new technology. As a result of this technology adoption, the customer-brand relationship can be increased. Therefore, it could be argued that these indicators are important to increase the customer-brand relationship.

3.2.3 Perceived ease of use on customer attitude towards AI chatbot

Due to the increasing popularity of online shopping, firms are constantly seeking new technologies to enhance customers' online brand experiences. Some authors have found that a system was be adopted if its use directly benefits the user (Rahmi et al., 2018). In another study, Rose and Fogarty (2006) also found that perceived ease of use directly affects the attitude toward the intention to use self-service systems. They found that when customers perceive ease of use with a self-service system in mobile banking, they develop a more positive affective attitude, mainly because of the faster response times compared to human workers. This, in turn, significantly influences perceived ease of use and citizens' affective attitudes toward their behavioral intention to use the service. Gunawan et al. (2019) stated that in e-commerce when customers perceive ease of use with a chatbot, they are more likely to have a positive attitude toward using the service. Therefore, it could be argued that perceived ease of use is an important indicator of increasing customer attitude and brand relationship.

3.2.4 Perceived usefulness on customer attitude towards AI chatbot

Many studies have examined the relationships between perceived usefulness and attitude in e-commerce. For instance, Gunawan et al. (2019) noted that customers are willing to use their mobile phones to purchase products in e-commerce applications when the applications are more beneficial. This is because the perceived usefulness of e-commerce can positively influence an individual's affective attitude toward the new technology. Customers adopt the functional mobile banking system, which can significantly influence their attitude to continue using it (Li & Shin, 2023). Further, they have demonstrated that customer-perceived usefulness, such as a positive attitude, can reinforce good performance and benefits. Customers will be positively impacted by perceived usefulness, and workers will also be affected. The perceived usefulness influences this positive attitude toward the technology (Ghaniabadi, 2024).
Furthermore, several studies have assessed the impact of perceived usefulness on customers' attitudes toward chatbots. For example, Soares et al. (2022) found significant positive effects of perceived usefulness on attitudes toward using chatbots as digital assistants in e-commerce sites. They argue that customers will likely develop an affective attitude toward the chatbot service if they perceive it as more valuable. Therefore, it could be argued that perceived usefulness becomes an important indicator of increasing customer attitude and brand relationship.

3.2.5 Attitude toward AI Chatbot and Customer–Brand Relationship

Attitude has been considered an essential variable in bridging the technology adoption and customer-brand relationship in this research, especially for the second stage of affective attitude. Based on the literature review, attitude has three stages: cognition, affective, and behavior. According to the ABC model, an affective attitude can boost brand reactions from consumers. As a result, past studies have studied customers' affective attitudes that influence customer-brand relationships in many contexts, such as advertisement, social media (Abzari et al., 2014), and the hotel industry (Nguyen et al., 2022). For instance, with the rise of social media, recent studies have also identified the effect of communication on customer attitudes toward a brand. Besides, (Lin & Wu, 2023) studied self-service and found that customers' attitude toward mobile banking systems impacts the customer-brand relationship. They reasoned that customers prefer to use self-service because it can satisfy their needs. Furthermore, Nguyen et al. (2022) said customers' attitude towards the AI chatbot easily influences customer-brand relationships in the hotel industry. They reasoned that many hotels used AI technology to increase efficiency and satisfy their customers' attitudes.

Considering the previous literature review, it could conclude that customer-brand relationships consist of three dimensions: satisfaction, brand trust, and commitment. For example, Jin and Youn (2023) found that affective attitude influences brand satisfaction toward the AI chatbot. The affective attitude contributing to how people feel about a chatbot was examined by (Han et al., 2018). They found that a positive hedonic experience is crucial to forming an attitude, affecting brand satisfaction, trust, and commitment. According to Bergner et al. (2023), when applied to a branded chatbot, the attitude as an emotional response to the shopping experience predicts long-term brand commitment. They advocated that making consistent efforts towards developing a satisfying experience is the outcome of customer attitude. Similarly, many firms aim to enhance customers' favorable attitudes toward their brands to increase customer satisfaction (Kim et al., 2016).

Furthermore, attitude theory is also mentioned in the literature review, which states that an individual behaves in ways aligned with his/her attitude. According to Davis (1989) and further expanded by Venkatesh and Davis (2000), perceived ease of use and perceived usefulness are core beliefs in the Technology Acceptance Model (TAM), representing cognitive evaluations that significantly influence users’ attitudes toward adopting a technology. Also, Ahn and Back (2020) mentioned that a practical attitude can lead customers to build a long-last relationship with this brand. This is because the affective attitude enhances the bonding with the brand.

Combining these hypotheses, a model is given to show how external factors affect how customers perceive the TAM models. This study emphasizes the impact of consumer attitudes on the customer-brand relationship. Figure 3.4 presents this model.

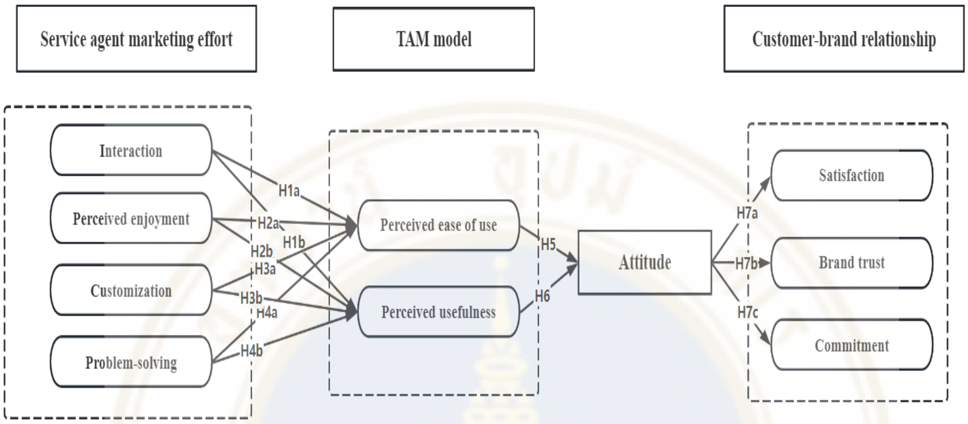

Figure 3.4 The proposal hypotheses of the AI chatbot

3.3 Research Methodology

The research employed research methods involving a literature review from theoretical and empirical perspectives. These methods are considered to identify and interpret existing research relevant to the research topic. This could help to provide a comprehensive understanding of the knowledge in the relevant field (Jayawardena et al., 2023). The theoretical literature review consists of established theories and concepts, while the empirical literature review focuses on analyzing data and findings from previous studies. This dual approach enables researchers to summarize existing literature and identify patterns, trends, and gaps in knowledge. Through critically evaluating a wide range of sources, researchers can build a strong theoretical foundation and formulate research questions grounded in existing evidence (Reyes et al., 2023).

Furthermore, this research methodology could also increase the credibility and validity of the study findings, enhancing knowledge within the field. Therefore, a study has formulated this research methodology. The conceptual model development literature review process has been formulated in Figure 3.5 below.

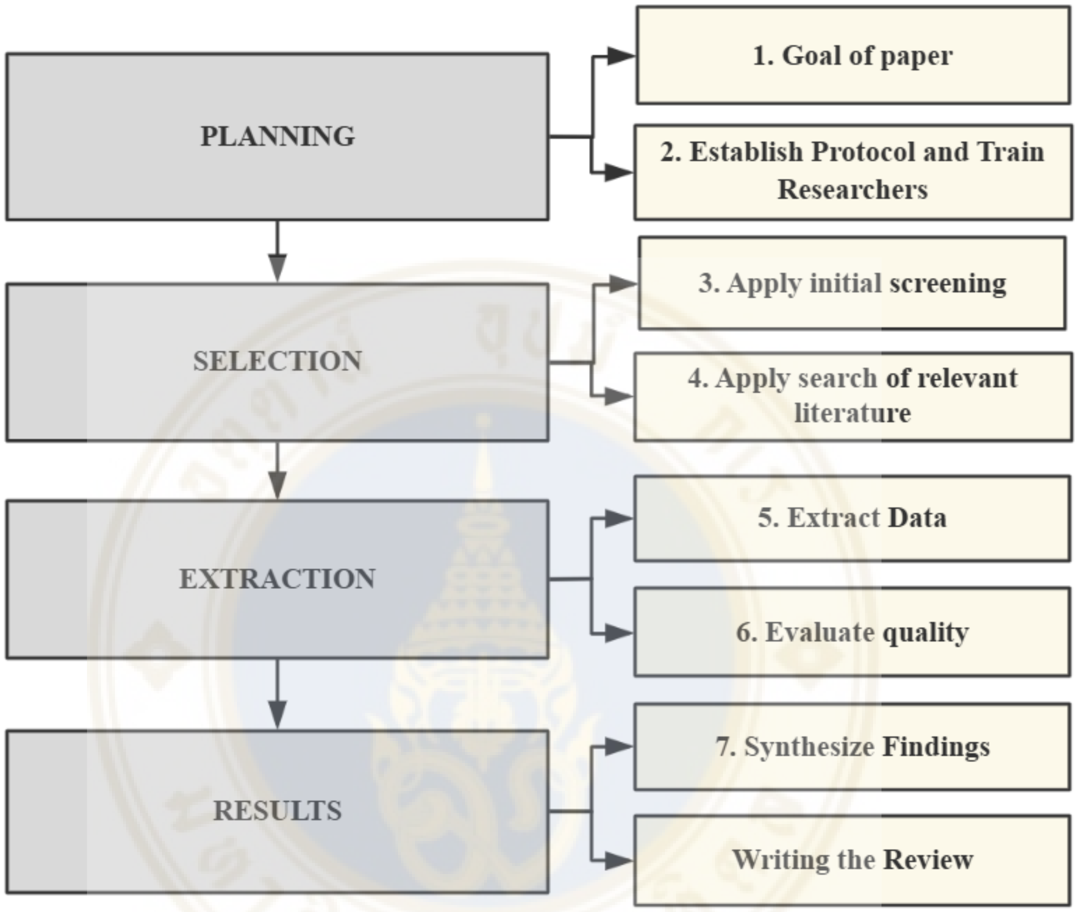

Figure 3.5 The phases and steps in conceptual framework Development

3.4 Results and Discussion

The behavioral expression represented by the customer-brand relationship reflects the behavioral response to the experiences customers have with the AI chatbot employed by a particular brand. This shows that when customers have a positive attitude towards the AI chatbot, the customer-brand relationship increases. Therefore, this research aimed to explore AI chatbot applications as e-service agents (interaction, perceived enjoyment, customization, and problem-solving capabilities) and their impact on customer brand relationships by increasing the positive attitude of customers.

Through employing the TAM), researchers examined how specific characteristics of AI chatbots, such as interaction, perceived enjoyment, customization, and problem-solving abilities, influence customer perceptions and attitudes. E-service agent market efforts comprise perceived enjoyment, customization, interaction, and problem-solving, which influence the TAM indicators, supported by (Lewis et al., 2019) research that AI tools are a good platform for performing functional dimensions and relationship dynamics in service. Consumers emotionally anticipated that marketers would make their online encounters enjoyable or entertaining (Fernandes & Moreira, 2019). These findings showed that chatbot characteristics are important indicators for improving perceived ease of use and usefulness.

Perceived ease of use and usefulness are important indicators of increasing the positive attitude of customers towards AI chatbots. Similarly, Al-Adwan et al. (2023) further demonstrated that the TAM model, particularly in terms of perceived ease of use and usefulness, positively influences students' attitudes toward using applications for online studying. In the context of AI chatbots, perceived ease of use ensures that customers find the technology approachable and user-friendly, while perceived usefulness reinforces the value that chatbots bring to customer interactions. Due to this research, the study uses AI chatbots as the new technology, which is necessary to maintain the ease of use and perceived usefulness of this study. Therefore, these distinctive perspectives, such as offering clients practical features via mobile messaging apps, have expanded the body of evidence from clever responses (Hohenstein & Jung, 2020). Therefore, it could be argued that customers' perception (e.g., perceived usefulness, ease of use, and trendiness) of using AI chatbots is also important.

Moreover, researchers reveal that attitude's affective component is a significant predictor of customer-brand relationship outcomes. Ajzen and Kruglanski (2019) found that attitude positively influences customer-brand development in the chatbot. This discovery emphasizes the importance of attitude in technology-mediated interactions. For this purpose, the study enriches the theory of attitudes using the A-B-C model, which is comprised of three components: affective, behavioral, and cognitive components (Ajzen & Fishbein, 1975). Further results show that attitude bridges the TAM model with customer-brand relationships. The AI chatbot is a new technology that studies and finds user attitudes founded on beliefs, and those cognitive or affective beliefs can influence behavior. This model's findings in previous literature show that perceived ease of use and perceived usefulness positively and significantly impact attitude. Therefore, these findings showed that customers' perception of the technology's ease of use and usefulness, as well as how they believe it is trustworthy, represents the cognitive component of attitude. This is because cognitive attitude means how customers process information about the attitude object, reflecting their beliefs and thoughts about their AI chatbot use (Eagly & Chaiken, 1993). Then, the affective component of customer attitude is represented by customer attitude in this study, representing their feelings or emotional reactions to an experience, which is then expressed through customers' actions towards the attitude object (MacKenzie & Lutz, 1989). Therefore, it could be argued that in chatbots, perceived ease of use and perceived usefulness become important indicators to increase the customer's relationship.

The findings literature shows that interaction has a significant positive relationship with customer brand relationship through customer trust. These findings showed that interaction with chatbots plays an important role in shaping customer attitudes toward brands within the TAM framework. In this regard, it could be explained that interactive features enhance user engagement and satisfaction, enhancing positive brand perceptions. Chatbots, through their conversational interfaces, provide opportunities for personalized interactions, addressing customer queries and needs in real-time. Studies by (Chi, 2018; Tran et al., 2023) highlight how interactive elements on digital platforms contribute to stronger brand relationships by enhancing user experiences and attitudes. Further literature shows that perceived enjoyment also significantly and positively influences customer-brand relationships through customer trust. Findings consistent with (Jami Pour et al., 2023; Won et al., 2023) demonstrated that enjoyable experiences with technology lead to favorable attitudes and increased importance of perceived enjoyment in the TAM framework that could enhance customer brand relationships. Customization also positively and significantly influences customer brand relationships within the TAM framework. These findings show that Chatbots can offer personalized experiences by tailoring interactions based on user preferences and past behavior. Studies by (Sharma, 2023; Tran et al., 2023) emphasize how customization strengthens brand connections by catering to individual needs and preferences, ultimately enhancing user satisfaction and attitudes toward the brand. Lastly, effective problem-solving of chatbots is also a significant predictor of the customer-brand relationship through improving attitude towards the brand. These findings within the chatbot showed that perceived usefulness and ease of use in the TAM model are key determinants of technology acceptance. Chatbots that efficiently resolve customer issues and queries enhance perceived usefulness, thereby improving attitudes towards the brand. Research by (Chon et al., 2022; Chon et al., 2023) emphasizes the importance of effective issue resolution in building trust and loyalty, aligning with the TAM's focus on factors influencing user perceptions and attitudes.

3.5 Implications

3.5.1 Theoretical Implications

The researchers integrate the A-B-C model, which includes cognitive, affective, and behavioral components, providing a nuanced understanding of how various external factors influence customer perceptions to build customer-brand relationships. Specifically, the proposed framework contributes to interaction, perceived enjoyment, problem-solving, and customization which are crucial in shaping affective attitudes, which drive customer brand relationships. The theoretical contributions of this research are substantial. By extending TAM to the context of AI chatbots, researchers offer a robust framework for understanding how these technologies can be leveraged to enhance customer-brand relationships. Besides, this research also expands the knowledge of customer-brand relationships by assessing itself (commitment, brand trust, and satisfaction) antecedents (i.e., e-service agent market effort, TAM model, and attitude) in the AI chatbot. However, the existing literature still lacks a complete picture of the factors that may affect the current customer-brand relationship in the AI chatbot. For example, Cheng and Jiang's (2022) study focuses on customer response to brand preference, brand loyalty, and purchase intention. The researchers focus on choosing a specific brand from many competing brands. Thus, our work focuses on the knowledge of CBR in AI chatbots with brand commitment, trust, and satisfaction. Many marketing efforts supplied to customers, such as perceived enjoyment, interaction, customization, and problem-solving, could reach a high degree, conceptualizing customer satisfaction, brand trust, and commitment and eventually building a relationship with the brand. This study contributed to the importance of chatbot marketing in digital relationship development.

3.5.2 Practical Implications

From a managerial perspective, this framework offers conceptual guidance for firms implementing AI chatbot technologies. It identifies important design characteristics—such as interaction, perceived enjoyment, customization, and problem-solving—that may enhance users' perceptions and encourage deeper engagement with the brand. Besides, companies must be careful to ensure that the personalization of their marketing engagement plays a significant part in influencing customers' perceptions while using chatbots to offer help and interact with their customers. Therefore, the study model could help businesses employ chatbots to gather data about customers' preferences and provide customized services. Furthermore, creating a suitable customer-brand relationship might significantly increase customers' likelihood of reusing the service. The important role of affective attitudes in the efficacy of AI chatbots for customer perception and relationship development cannot be overstated. When AI chatbots are deliberately crafted and programmed to embody an affective attitude, AI chatbots can proficiently establish emotional connections with customers. This emotional resonance not only attracts a more extensive customer base but also fosters enduring relationships between the customer and the AI chatbot. An affective attitude in an AI chatbot can elevate customer behavior, heighten satisfaction levels, and ultimately engender customer loyalty. Hence, the deliberate implementation of an affective attitude in AI chatbots stands as a strategic imperative, offering the prospect of expanding customer bases and fortifying enduring relationships to the ultimate benefit of businesses. Literature also cited that managers could implement strategies to strengthen customer bonds as the connection develops (Kaufmann et al., 2020). Therefore, the study model using the TAM approach could help to increase the positive attitude that could increase the customer-brand relationship with the companies.

3.5.3 Limitations and further study

As an intelligent system of natural language interaction with humans, chatbots are widely used in customer service, information queries, educational assistance, and other fields. The study focused on AI chatbots within e-service contexts, which may be limited to other contexts, such as healthcare, education, or entertainment. The researchers explores the role of AI chatbots across various industries to determine if the identified relationships hold in different settings in the future. Moreover, chatbots' service quality and interaction experience are important factors in studying the customer-brand relationship with AI chatbots. Thus, the researchers would like to study the level of service quality and customers' experience. As chatbots become more prevalent, users' expectations for seamless and satisfactory interactions will continue to rise. Poor service quality from chatbots can lead to frustration, dissatisfaction, and ultimately abandonment of the technology. Chen et al. (2022) applied that service quality includes efficiency, continuous improvement, and cultural adaptation. By actively studying and investing in improving the service quality of AI chatbots, organizations can meet user expectations, enhance task completion and efficiency, deliver superior user experiences, build trust and credibility, gain a competitive advantage, enable scalability and consistency, and drive innovation in this rapidly evolving field. Moreover, as chatbot interactions shape customers' perceptions of a brand, a positive customer experience with a chatbot can enhance brand reputation and foster trust. Thus, customer experiences help businesses understand how their chatbots are perceived and take appropriate measures to maintain a favorable brand reputation. By prioritizing and continuously improving the customer experience, businesses establish themselves as industry leaders in customer service and engagement. Moreover, the researchers may study repurchase intention and electronic word-of-mouth (eWOM) as observable behavioral outcomes that extend the customer-brand relationship construct. This will enable us to better understand how internal psychological states—such as trust, satisfaction, and commitment—lead to measurable brand-supportive actions with the AI chatbot in the future. Therefore, in the future, the researchers may include the level of service quality and customer experience in the study.

3.5.4 Conclusion

The research aimed to explore the application of AI chatbots as e-service agents and their impact on developing customer-brand relationships employing Technology TAM and the A-B-C model to understand how specific chatbot characteristics shape customer perceptions and attitudes. The objectives showed that perceived enjoyment, interaction, problem-solving, and customization significantly affect attitudes that increase customer brand relationships. Findings align with previous TAM research and emphasize the importance of perceived ease of use and perceived usefulness in shaping attitudes toward chatbots. Additionally, the study emphasizes the role of affective attitudes as significant predictors of customer-brand relationship outcomes, bridging the TAM model with customer-brand relationship theory. This research contributes to a deeper understanding of how AI chatbots influence customer perceptions and attitudes, highlighting the importance of these technologies in fostering positive brand relationships. The future could be addressed with a quantitative approach

CHAPTER IV
NAVIGATING THE DIGITAL FRONTIER: EXPLORING THE DYNAMICS OF CUSTOMER-BRAND RELATIONSHIPS THROUGH AI CHATBOTS

This chapter presents the empirical validation of the conceptual framework and hypotheses developed in Chapter 3. Based on the theoretical foundations and proposed model, a structured mixed methodology was employed to collect and analyze data related to users' interactions with AI chatbots and their impact on customer–brand relationships. The primary objective of this chapter is to examine the strength and direction of the hypothesized relationships through qualitative and quantitative statistical testing.

4.1 Introduction

With technology development, artificial intelligence (AI) has drastically reshaped how businesses interact with customers, mainly through AI-driven chatbots. These virtual assistants deliver fast, personalized, and efficient interactions, making them indispensable in modern customer service strategies. Besides, The emergence of artificial intelligence (AI) chatbots has revolutionized brand-customer interactions, offering unique opportunities to cultivate relationships through personalized and intelligent conversations (Chen et al., 2022). The rise of Artificial Intelligence (AI) has profoundly transformed business operations across various industries, including marketing, digital healthcare, and educational technology (Cheng & Jiang, 2020a). However, many studies found that chatbots are effective in customer service strategies.

AI chatbots are computer programs that simulate human-like conversations using natural language processing (NLP) and machine learning (ML) technologies (Xu et al., 2021). These virtual assistants engage in seamless user interactions, understanding and responding to customer inquiries, providing personalized recommendations, and offering real-time support, thus transcending the limitations of traditional customer service channels. Moreover, AI chatbots can potentially create perceived enjoyment for users by incorporating humor and engaging conversational styles (Goli et al., 2023). This enjoyment factor increases user satisfaction and a more positive attitude toward the chatbot and its associated brand (Lee et al., 2022).

Customization is another critical characteristic of AI chatbots, as they can tailor their responses and recommendations based on individual user preferences, purchase history, and contextual data (Davies et al., 2020). This personalized approach ensures that each interaction is tailored to the user's needs, fostering a sense of exclusivity and enhancing the overall customer experience. Besides, AI chatbots excel at problem-solving by leveraging their vast knowledge bases and advanced NLP capabilities. Xu et al. (2020) found that AI chatbots assist users in resolving queries, troubleshooting issues, and providing relevant information or recommendations, effectively addressing customer pain points and enhancing overall satisfaction.

The adoption and effectiveness of AI chatbots are influenced by various theoretical models, including the Technology Acceptance Model (TAM) (Linh & Wu, 2023). The TAM emphasizes perceived ease of use and usefulness as critical determinants of technology acceptance, suggesting that users are more likely to adopt and embrace intuitive, user-friendly chatbots, which offer tangible benefits.

Customer attitudes towards AI chatbots are pivotal in shaping the overall customer-brand relationship. Positive attitudes, driven by perceived ease of use, usefulness, and trust, can increase customer satisfaction, brand trust, and commitment (Cheng & Jiang, 2022). Ultimately, the success of AI chatbots lies in their ability to enhance the customer-brand relationship by fostering satisfaction, building brand trust, and nurturing long-term commitment. Satisfied customers who perceive the chatbot as trustworthy and reliable develop a stronger emotional connection with the brand, leading to increased loyalty and advocacy. To reach this study's overall goal and investigate how a brand can devise a chatbot to nurture its customer-brand relationship. However, existing research has concentrated mainly on chatbots' technological and operational facets, with limited emphasis on understanding how chatbot interactions affect customer attitudes, satisfaction, and commitment (Naudé, 2019). Although the characteristics of AI chatbots—such as interaction, customization, problem-solving, and perceived enjoyment—are recognized as vital for engagement, few studies have empirically examined how these factors influence the development of long-term customer-brand relationships (Kim & Ko, 2012; Ladhari, Souiden, & Dufour, 2017; Huang & Rust, 2018). Therefore, this study seeks to address these research gaps by exploring how AI chatbots can positively impact customer-brand relationships, focusing on the Chinese market.

In order to bridge the gaps, this study adopts a mixed-methods research design to understand how AI chatbots influence customer-brand relationships comprehensively. First, the qualitative analysis phase is to guide hypothesis formation. In this respect, the in-depth interviews with users of AI chatbots reveals specific factors that affect customer's perceptions and attitudes toward AI chatbots. These themes provide a basis for developing and testing quantitative hypotheses. Then, the quantitative analysis tests the hypothesized relationships between chatbot characteristics, customer perceptions, attitudes, and brand relationships. The Technology Acceptance Model (TAM) serves as the theoretical foundation for this research, helping to identify key constructs such as perceived ease of use, perceived usefulness, and trust. The mixed-methods approach provides a holistic view, enabling the study to address both the exploratory and confirmatory aspects of customer perceptions and attitudes toward AI chatbots in the Chinese market context.

4.2 Conceptual Background

4.2.1 E-service Agent Effort

AI chatbots are launched as e-service agents, which can eliminate physical and temporal distance by providing clients with simple access to product information 24/7 (Zhang & Dholakia, 2018). Some other studies (Chung et al., 2020; Cheng & Jiang, 2022) present that there are five essential sub-dimensions in e-service agents, which are interaction, information, accessibility, entertainment, and customization, and updated literature on chatbots' applicability across sectors to deepen the conversation. However, in this study, according to Alharbi (2020), AI chatbots can increase brand performance, including interaction, perceived enjoyment, customization, and problem-solving. Thus, the research studies those four characteristics: interaction, perceived enjoyment, customization, and problem-solving.

Interaction represents online contact between customers and AI chatbots via the internet (Ciechanowski et al., 2019). Oladele et al. (2022) refer to customer-brand interaction as encompassing all the communication between a brand chatbot and a customer. AI chatbots as e-service agents enable organizations to make efficient customer contact, enhancing customers' brand experience. Perceived Enjoyment refers to how an individual finds an activity or interaction enjoyable or satisfying (van der Heijden et al., 2001). In the context of technology and user experience, perceived enjoyment is a critical factor influencing users' willingness to adopt and continuously engage with a system or product. It emphasizes the intrinsic pleasure or positive feelings that arise from using a particular technology or service, enhancing user motivation and fostering a positive attitude toward future interactions. Customization refers to personalizing products, services, or interactions to meet individual user preferences and needs, thus enhancing user experience and satisfaction (Mourtzis, Vlachou & Milas, 2016). In AI-driven customization, algorithms analyze user data, behaviors, and preferences to adapt real-time content, recommendations, and functionalities, fostering greater engagement to strengthen the relationship between users and AI-enabled platforms. Problem-solving defines a problem and determines its primary cause, choosing potential solutions and putting them into action to help customers (Van Aken & Berends, 2018). Through advanced data processing, pattern recognition, and predictive analytics, AI assists users and organizations in identifying root causes, exploring solutions, and implementing strategies with precision and speed. AI-driven problem-solving enhances decision-making by generating actionable insights, automating repetitive tasks, and continuously learning from outcomes, which enables adaptive and fosters wider AI adoption in business (Dixon, 2010).

4.2.2 TAM model

Adoption refers to a person voluntarily choosing to employ new technology (Carter & Belanger, 2005). TAM's primary basic constructs are perceived usefulness and ease of use (Davis, 1989). Perceived ease of use describes how users perceive that using technology requires little effort, making it simple (Davis, 1989). Perceive usefulness refers to how users believe using a particular technology will improve their performance (Hartono & Edward, 2014). Furthermore, perceived usefulness and perceived ease of use, which are applied in various technical situations, are the two fundamental constructs that makeup TAM.

Since then, it has been adopted by many scholars in various contexts of technology usage. For example, Marsh and Poepsel (2008) examined online studying tools. Their study has found that the perceived usefulness of online studying tools can develop students' interests and skills. Users' perceptions of how beneficial and easy to use a chatbot is will significantly influence their acceptance and utilization of the technology (Gunawan & Nugroho, 2019; Iriani & Andjarwati, 2020; Rajmi, Burak & Adnan, 2018). Chen and Aklikokou (2020) proposed that focusing on the fundamental factors of perceived ease of use and usefulness when implementing AI technology will ultimately increase customer acceptance of such services. Similarly, Liang, Lee, and Jane (2020) underlined that with the growing interest in digital innovations, the two factors are critical to understanding how customers respond to new technologies, especially artificial intelligence (AI) and its application (i.e., chatbot).

4.2.3 The Theories of the Cognitive-Affective-Behavior Model

Customer attitudes combine a person's beliefs, sentiments, and behavioral intentions toward a firm (De Ruyter, Wetzels & Kleijnen, 2001). Ajzen and Fishbein (1977) say a person with a favorable attitude toward action is likelier to engage in a particular behavior. Customer attitude thus plays an essential role in evaluating alternatives and selecting a specific product brand so that the customer can satisfy his needs. Attitudes comprise three components: cognitive, affective, and behavioral (Ajzen, 1989). An excellent illustration of a subject where attitudes are built on beliefs is technology. Fishbein and Ajzen (1975) said that beliefs, whether cognitive or affective, can have an impact on behavior. Lavidge and Steiner (1961) proposed that when clients are exposed to persuasive advertising communication, the process leading to product acquisition is characterized as a transition from the cognitive to the affective and behavioral stages. The cognitive component of attitude focuses on how cognition influences a person's attitude toward a psychological entity, such as technological concepts and thoughts.

In contrast, the affective stage includes a person's trust in technology. Perceived trust is a unique aspect of the affective dimension; although it is categorized as an affective form, trust also has a cognitive component. This suggests that trust can change and evolve as individuals acquire new information over time, shifting from situational to enduring trust (Glikson & Woolley, 2020). Cognitive engagement encompasses two main factors – attention and absorption (Rothbard, 2001). Attention revolves around the individual psychological engagement process, which determines the allocation of personal attentiveness toward a brand (Kahneman, 1973).

This study argues that customers' perceptions of perceived usefulness and perceived ease of use for the technology represent attitude's cognitive component. Then, the affective component of customer attitude is represented by customer attitude in this study, representing their feelings or emotional reactions to an experience, which is then expressed through customers' actions towards the attitude object (MacKenzie & Lutz, 1989). Moreover, the customer-brand relationship in terms of brand satisfaction, trust, and commitment reflects the behavioral response to the experiences customers have with the AI chatbot.

4.2.4 Customer-brand relationship

The branding literature has long emphasized customer-brand relationship (CBR). Fournier (1998) proposed that the customer-brand relationship comprises commitment, intimacy, and self-connection. Later, Zhang and Bloemer (2008) conceptualized the customer-brand relationship as a multi-dimensional construct comprising satisfaction, trust, and emotional commitment. This conceptualization of customer-brand relationships has then been adopted by several studies (Kim & Ko, 2010; Cheng, 2020). Thus, this research studies CBR as a sub-dimensional construct represented by three dimensions: 1) satisfaction, 2) brand trust, and 3) commitment.

Oliver & Swan (1989) defined satisfaction as the extent to which behavior outperforms, needs to meet, or fails one's expectations. In adopting AI, Mimoun et al. (2017) found that some fashion firms provide information to their customers using chatbots to assist in minimizing ambiguity and boosting customer satisfaction. Indeed, effective customer-chatbot interactions should enable a service brand to satisfy its customers and develop a relationship. Brand trust can be another necessary construct in customer-brand relationships. Garbarino and Johnson (1999) defined brand trust as a psychological attachment. Through the practical design of AI chatbots, customers can become more confident, making them more willing to develop a relationship with the brand (Keiningham et al., 2017). Similarly, Mabkhot et al. (2017) found that customers' perception of their interaction with the chatbot shapes their brand trust.

Besides, Chen et al. (2023) define commitment as customers' emotional attachment to a particular object, such as a brand. The length of time represents that customers are willing to stay and maintain the relationship with the company or the brand. Prentice et al. (2020) mentioned that if customers expect to engage with AI tools or services, this behavior will make them commit to the AI service. As the e-service agent is now gradually replaced by chatbots, Araújo & Casais (2020) stated that customers' buying behavior changes when they use chat applications such as shopping-assistant chatbots. Because of the high level of technology and interesting functions, customers are dedicated to the shopping assistant chatbots and can feel emotional attachment when interacting with them.

4.3 Study I: Conceptualization of AI Chatbot Usage

Formulating suitable research strategies or design plans is an essential aspect of research activities. The research design includes a structure for data collection, reliable measurement, and analysis (Saunders et al. 2003). Moreover, a crucial task for this research is to define the aim of the research. This study focuses on the technology adoption model (TAM: Davis, 1989) to explain how the four characteristics of the chatbot influence the customer perception. Besides, many researchers studied TAM in a range of cultures, however, these antecedents of AI chatbot still lacks of study.

Furthermore, individuals form an attitude toward a particular object of their interaction (Ajzen & Kruglanski, 2019). Their attitude then guides their behavior (VanMeter et al., 2018). Thus, this study also incorporates customer attitude to explain why the chatbot can lead to a successful customer-brand relationship. However, most studies have been conducted in the Western context (Parasuraman, Cosenzo, & de Visser, 2009; Ajzen & Kruglanski, 2019; Rajasshrie, 2020). Thus, cultural differences between Western and Chinese customers may affect the scale measurement adapted from past studies (Drasgow & Hulin, 1987). Moreover, customers' behavior differs significantly between East and West countries. Anderson & He (2006) studied that Western customers' behavior may not accurately forecast conduct compared with Eastern customers. In Western countries, customers focus on service quality and personal brand preferences (Mou & Benyoucef, 2021). However, customers in Eastern countries tend to brand reputation and external features. Besides, Pekovic & Rolland (2020) found that qualitative analysis can help researchers find customers' fundamental attitudes, beliefs, and motivations. Thus, using qualitative analysis in this research helps researchers to understand the chatbot characteristics and their customers' behavior and shape their attitude toward AI chatbots in Eastern countries' context.

Addressing confirmatory questions with quantitative methodologies and deductive reasoning may lead to a deeper understanding of the phenomenon under study, while addressing exploratory questions with qualitative methodologies and inductive reasoning may reduce validity concerns that may arise when using a single methodology (Leppink, 2017). In consumer behavior research, mixed approaches have been proven to be very helpful (Tashakkori & Teddlie, 2009).This study began with qualitative research to allow researchers to gain in-depth insights and understanding of human behavior and attitudes. Researchers can uncover rich and nuanced data that cannot be captured through quantitative means alone by utilizing qualitative methods, such as interviews, focus groups, and observations in the context of developing an AI chatbot; qualitative analysis can provide valuable information about user preferences and needs, ultimately informing the design and improvement of the chatbot's functionality and user behavior. In this section, the researchers explores how qualitative analysis can be integrated into the more extensive mixed methodology approach to AI chatbot development, providing practical guidance and best practices for leveraging qualitative data to enhance the chatbot's effectiveness.

4.3.1 Sample and Data Analysis

The selection of informants to be interviewed is a crucial aspect of the research process. Informants can be classified based on several criteria, and the selection of participants is mainly influenced by the nature of the project (Solarino & Aguinis, 2021), as the research is to study the customers who used the Alipay chatbot before and have experience with the chatbot in Nanjing, China. The researchers use snowball sampling to recruit participants with prior experience using the Alipay AI chatbot. Researchers carefully choose individuals with distinctive features or unique experiences relevant to using the Alipay chatbot. The purpose is to discover and enroll individuals who can help improve the study findings. Thus, based on the snowball sampling technique, the researchers choose the appropriate characteristics of participants for using an AI chatbot. First, the informants should be familiar with technology and comfortable using digital tools. Second, the informants' language proficiency and ability should communicate effectively in the language used by the chatbot as educated users are more likely to have encountered chatbots and possess the ability to articulate their experiences. Third, their specific knowledge or expertise related to the topic or purpose of the AI chatbot. Fourth, they must be available and willing to engage with the chatbot actively.

Participants should also clearly understand the AI chatbot's purpose and benefits. Englander (2022) mentioned that various circumstances determine the number of key informant interviews required for a qualitative case study, and no fixed number is considered sufficient. Indeed, when considering the appropriate sample size, the research should aim for the objectives, available time, and resources. De Los Reyes et al. (2013) studied using 15 to 25 informants to measure the data needs, which is the most appropriate number. Creswell and Poth (2018) emphasize that phenomenological research generally involves a sample size ranging from 5 to 25 participants, which is considered sufficient to yield rich, in-depth accounts of individuals' lived experiences. Similarly, empirical studies by Guest, Bunce, and Johnson (2006) as well as Francis et al. (2010) support the notion that thematic data saturation frequently occurs between 12 and 20 interviews. Guest et al. (2006) specifically found that the emergence of novel information declined substantially after 12 interviews, with complete saturation typically achieved prior to reaching 20 participants. Thus, the researchers interviewed 20 informants in Nanjing using AI chatbots. Table 1 shows the demographic information for using the AI chatbots.

The qualitative interviews were conducted with 20 informants, as shown in Table 4.1, across various professions, such as teachers, financial analysts, managers, etc. The study focuses on service agent marketing efforts, the Technology Acceptance

Model (TAM), and customer-brand relationship constructs. In this analysis, we use the qualitative findings to examine the significant relationships illustrated in the conceptual framework, focusing on the components such as interaction, perceived enjoyment, customization, problem-solving, perceived ease of use, perceived usefulness, attitude, and customer-brand relationship dimensions like satisfaction, trust, and commitment.

Table 4.1 Demographic information of informants.

Number	Name	Age	Gender	Education	Position
1	Informant A	27	Male	Bachelor	Teacher
2	Informant B	32	Male	Master	Manager
3	Informant C	29	Female	Master	Doctor
4	Informant D	30	Female	Ph.d	Student
5	Informant E	31	Male	Bachelor	Lawyer
6	Informant F	27	Female	Bachelor	Teacher
7	Informant G	23	Male	Master	Doctor
8	Informant H	33	Male	Master	Teacher
9	Informant I	37	Male	Bachelor	Lawyer
10	Informant J	35	Female	Bachelor	Manager
11	Informant K	32	Female	Bachelor	Lawyer
12	Informant L	42	Male	Ph.d	Manager
13	Informant M	20	Female	Bachelor	Student
14	Informant N	33	Male	Master	Manager
15	Informant O	45	Male	Bachelor	Businessman
16	Informant P	31	Female	Master	Financial analyst
17	Informant Q	26	Female	Master	Financial analyst
18	Informant R	21	Male	Bachelor	Student
19	Informant S	30	Male	Bachelor	Businessman
20	Informant T	29	Female	Bachelor	Businessman

4.3.2 Data analysis and result

The qualitative research phase adopted semi-structured in-depth interviews to investigate the factors contributing to the Technology Acceptance Model (TAM) and the consumer brand relationship associated with Alipay chatbot services in China. Using in-depth interviews allowed the researcher to better understand their attitude toward AI chatbots in China. That is because semi-structured interviews gather data that accurately represent the participants' perspectives without confining them to a predetermined set of responses, as is typically observed in a structured questionnaire survey (Sooful, Surujlal, & Dhurup, 2010; Wiid & Digginess, 2011; Englander et al., 2022).

Formulating interview questions is fundamental to interview design (Turner, 2019). The interview guide was developed after an extensive examination of relevant scholarly literature (Sidaoui, Jaakkola & Burton, 2020; Nadarzynski et al., 2021; Seitz, Bekmeier-Feuerhahn & Gohil, 2022). The qualitative inquiries examined several factors, including the e-service agent effort market, TAM, attitude, and customer brand relationship in the context of chatbot service. The qualitative interviews were conducted via WeChat video and part of informants conducted offsite. The study was conducted in English.

First, the analysis follows a thematic approach, which is particularly effective in identifying and categorizing recurring themes relevant to users' interactions with the chatbot. Second, the recorded interviews are transcribed verbatim, providing a rich dataset for analysis. Researchers then read transcripts to gain familiarity and identify initial codes that capture significant points or recurring ideas. These codes are then grouped into categories, revealing overarching themes related to interaction, perceived enjoyment, customization, and problem-solving. The next stage involves organizing these themes to highlight key insights about user preferences, challenges, and behavior patterns. Themes such as "ease of use," "usefulness," and "customer attitude" are identified and explored to understand the chatbot's impact on user behavior. The results are shown in Table 4.2. Additionally, the analysis identified two emergent themes: Emotional comfort – Participants described feeling reassured by quick responses and polite language, especially during financial service issues; Concerns over data privacy – Some users expressed hesitation about sharing sensitive information with an AI agent, despite convenience. However, several additional themes emerged beyond the scope of the proposed theoretical model—most emotional comfort and data privacy concerns. For instance, some participants described feeling reassured by the chatbot's polite tone and quick responses, particularly during financial service issues, indicating an effective response we refer to as emotional comfort. Others raised concerns about data privacy, expressing hesitation in disclosing sensitive information to an AI agent.

Based on results from interviews and literature review, AI chatbots enhance customer attitudes across multiple dimensions. First, the interaction capability allows chatbots to provide timely responses and improve accessibility to information, thereby enhancing customer-brand interaction. Secondly, perceived enjoyment increases user acceptance through convenience and time-saving features, while customization meets specific customer needs, making the experience more relevant. Additionally, problem-solving abilities enable chatbots to effectively handle common issues, reducing the need for human intervention and enhancing user satisfaction. In terms of perceived ease of use and usefulness, a simple interface design lowers the learning curve, and automation reduces the workload, positioning chatbots as efficient assistant tools. Positive user attitudes foster brand loyalty and satisfaction, further establishing trust and commitment, contributing to a long-lasting customer-brand relationship.

4.4 Study II Conceptual Framework and Hypothesis Development

Drawing from prior research and established theoretical frameworks, this study aims to expand TAM in the context of AI chatbots. It integrates service agent marketing efforts as an external factor shaping customer perceptions of AI chatbots. Based on TAM, the study posits that users' perceptions—specifically regarding the chatbot's ease of use and usefulness—are pivotal in shaping their attitudes. These attitudes, in turn, are hypothesized to be related with the formation of customer-brand relationships. The proposed hypotheses of the AI chatbot are in Figure 4.1.

Table 4.2 Dimensional Analysis of AI Chatbot Usage.

Axial codes	Examples of open codes from interview	Examples of open codes from literature review	References
Interaction	Provides timely responses and improves accessibility; Enhances efficiency in handling routine tasks; Reduces waiting time for information	Enhance customer engagement through interactive sessions; Utilize NLP to improve conversation flow; Support consistent brand-customer interaction, enhancing customer experience.	(Gnewuch et al., 2018; Oladele et al., 2022; Chung et al., 2020)
Perceived enjoyment	Convenient and time-saving; Allows quick access to information; Seen as a practical and efficient tool	Humor and engaging styles boost user enjoyment; Positive user experience impacts technology acceptance; Interactive features foster motivation to use.	(Goli et al., 2023; Lee et al., 2022; van der Heijden et al., 2001)
Customization	Can be customized to answer frequently asked questions; Allows some level of tailored responses; Meets general user needs effectively	Tailored interactions increase relevance; Real-time data-driven adjustments foster engagement; Customization adapts responses to user needs.	(Davies et al., 2020; Mourtzis et al., 2016; Zhang & Dholakia, 2018)
Problem-solving	Effective for addressing common questions; Provides immediate answers for simple issues; Reduces the need for human intervention in basic tasks	Assists with data-driven solutions; Reduces customer frustration by resolving minor issues; Enhances customer experience by addressing FAQs.	(Xu et al., 2020; Dixon, 2010; Van Aken & Berends, 2018)
Perceived Ease of use	Simple and user-friendly interface; Easy to navigate and accessible anytime; Reduces learning curve for new users	Ease of use influences user acceptance; A simplified interface increases adoption rates; Intuitive design improves customer experience.	(Davis, 1989; Chen & Aklikokou, 2020; Gunawan & Nugroho, 2019)

Axial codes	Examples of open codes from interview	Examples of open codes from literature review	References
Perceived usefulness	Reduces workload by automating repetitive tasks; Helps users save time on routine queries; Enhances productivity for routine activities	Facilitates access to information, improving performance; Reduces user frustration by providing quick solutions; Users view it as beneficial for quick responses.	(Hartono & Edward, 2014; Rajmi et al., 2018; Marsh & Poepsel, 2008)
Attitude	Viewed as a reliable assistant for routine queries; Appreciated for its accessibility and responsiveness; Considered helpful for quick information retrieval	Positive user attitudes enhance engagement; Attitude towards service influences customer loyalty; Favorable attitudes foster brand advocacy.	(De Ruyter et al., 2001; Ajzen, 1977; Crano & Prislin, 2011)
Satisfaction	Satisfies basic informational needs promptly; Reduces frustration with quick responses; High satisfaction with simple and efficient tasks	Satisfactory interaction improves brand loyalty; Customer satisfaction enhances customer-brand relationships; Fast responses fulfill customer expectations.	(Mimoun et al., 2017; Papista & Dimitriadis, 2012; Chen & Jiang, 2021)
Brand trust	Trusted for handling standard questions securely; Viewed as consistent and reliable for FAQs; Users feel confident in using it for routine inquiries	Brand trust is built through reliable interaction. Brand trust is crucial in service marketing. Clear communication fosters brand trust.	(Garbarino & Johnson, 1999; Atulkar, 2020; Mabkhot et al., 2017)
Commitment	Perceived as a dependable tool for regular tasks; Considered an integral part of service experience; Viewed as a valuable addition to customer support	Emotional attachment drives commitment; Customer dedication linked to reliability; Trust in tools fosters commitment.	(Prentice et al., 2020; Araújo & Casais, 2020; Keiningham et al., 2017)

4.4.1 Interaction and Perceived Ease of Use & Perceived Usefulness

Past studies (Alassafi et al., 2022; Taufik et al., 2019) have identified interaction as a key external factor influencing user perceptions of new technology. For example, Alassafi et al. (2022) discovered that when users perceive interactions as human-like, their perceptions of the ease of use and usefulness of e-learning systems can encourage continued usage. Indeed, they reasoned that good interaction between the students and the e-learning system can encourage continued usage. Similarly, customers seek interactions during their service consultation. When customers encounter a new technology, such as a self-check robot service, human-like interaction enhances their perception of its ease of use and usefulness (Taufik et al., 2019), thus facilitating the adoption of the new technology.

In addition, the interactive and two-way communication between customers and computer-mediated communication, such as a chatbot, leads customers to positively evaluate the technology's ease of use and usefulness (Alkali et al., 2017; Lee et al., 2013). Furthermore, researchers have found that past studies (Holzwarth et al., 2006;

Ladhari et al., 2020; Mollen and Wilson, 2010) indicated that when customers perceive their interactions with e-service agents such as AI chatbots to be courtesy, responsive, knowledgeable, and close to those with a human agent, they enjoy the interactions and find their interactions helpful for their purchasing decision process. Iwamura et al. (2011) investigated whether older users' interactions with robot agents influenced their purchase intentions. They found that effective interaction with the robot agent can increase the users' perceived ease of use.

H1a: Interaction positively influences perceived ease of use.
H1b: Interaction positively influences perceived usefulness

4.4.2 Perceived Enjoyment and Perceived Ease of Use & Perceived Usefulness

Perceived enjoyment has also been considered a key factor in explaining customers' technology acceptance on the internet in various settings. Past studies (Galatsopoulou et al., 2022) have found that customers' perceived ease of use and usefulness of new technology influence their positive attitudes towards it. For instance, educational research has consistently demonstrated a positive relationship between perceived enjoyment, usefulness, and ease of use (Sánchez-Prieto et al., 2016; Teo & Noyes, 2011). Similarly, Huang and Liam (2018) found that perceived enjoyment, as an external factor, positively influences perceived ease of use in educational contexts. They argued that a learning management system can positively enhance students' perception of enjoyment. Abzari et al. (2014) also suggested that perceived enjoyment influences students' perceptions of e-learning as easy to use. Students may show more interest in using an e-learning system if they find the system easy to manipulate.

Furthermore, the positive impact of perceived enjoyment on perceived ease of use has been observed in other contexts, such as mobile banking and social robots (Limakrisna & Moeins, 2024; Huang, 2017; Chien et al., 2019; Saif et al., 2024). For example, Limakrisna & Moeins (2024) found that a mobile banking interface can capture users' attention when using an online banking system. Saif et al. (2024) also added that users' perceived enjoyment is positively impacted when they use mobile banking and perceive its usefulness. Chien et al. (2019) mentioned that enjoyment significantly influences perceived ease of use when using the social robot. Indeed, according to Park et al. (2012), enjoyment can reduce users' panic when encountering new information systems. Thus, users underestimate the task's difficulty and evaluate their experience with the new technology. Users thus feel optimistic about the technology's ease of use and usefulness.

H2a: Perceived enjoyment positively influences perceived ease of use
H2b: Perceived enjoyment positively influences perceived usefulness

4.4.3 Customization and Perceived Ease of Use & Perceived Usefulness

Customization is also discussed as another external factor to explain technology adoption in various contexts, such as mobile banking (Albashrawi, 2021), digital marketing (Ansari et al., 2019), and online retailing (Zhang & Zheng, 2021). For example, customization has been found to substantially impact online retailers' perceived usefulness and ease of use (Bahtti & Bauirzhanovna, 2023). Joshi et al. (2021) studied how advanced technology in retail customized young customers' perceived ease of use and perceived usefulness in electronic retailing. Albashrawi (2021) also found in mobile banking that when customers perceive that the digital transaction system can be customized to fit their mobile banking behavior, they become familiar with the system. As a result, customers perceive the system as easy to use (Wijayaa et al., 2021) and find their experience using mobile banking helpful system (Lee & Chen, 2022).

H3a: Perceived customization positively influences perceived ease of use.
H3b: Perceived customization positively influences perceived usefulness

4.4.4 Problem-Solving and Perceived Ease of Use & Perceived Usefulness

Problem-solving is another factor in technology adoption across various sectors that can influence customers' perceived ease of use and usefulness. Research on adopting new technology suggests that the ability to solve problems plays a role in influencing customers' adoption decisions (Joksimovic et al., 2023). For instance, Lin

(2019) found that perceived usefulness and ease of use positively influence problem-solving with an innovative online learning application. Indeed, Huang & Liaw (2018) also identified that when users operate virtual reality technologies with various applications in education, they will be influenced to adopt them if they can solve the problems for the users. Indeed, an intelligent learning application can effectively solve problems in education learning. Similarly, Mohamed and Lamia (2018) learned about an intelligent tutoring system that can help teachers be easy to use to solve problems. Besides, some authors also found that AI chatbots are important in providing many solutions to influence customers' behavior to adopt (Chung et al., 2020; Sheth al., 2019), such as finding answers efficiently and using service much more quickly (Brandtzaeg & Følstad, 2017). This is because AI chatbots support a new layer function to solve customers' problems and influence their perception of the new technology.

H4a: Problem-solving positively influences perceived ease of use.
H4b: Problem-solving positively influences perceived usefulness

4.4.5 Perceived Ease of Use and Attitude (H5)

Due to the increasing popularity of online shopping, firms are constantly seeking new technologies to enhance customers' online brand experiences. Some authors have found that a system will be adopted if its use directly benefits the user (Rahmi, Birgoren & Aktepe, 2018; Chen & Aklikokou, 2020). For instance, Guritno & Siringoringo (2013) found that perceived ease of use positively affects attitudes toward the usability of online shopping, significantly shaping customers' attitudes toward online shopping. Iriani and Andjarwati (2020) also found that perceived ease of use positively influences attitude and intention to shop online during the COVID-19 pandemic. Hansen, Saridakis, and Benson (2018) further supported the hypothesis that perceived ease of use significantly amplifies the effect of customers' attitudes when using social networks for transactions. They argued that the TAM model, focusing on perceived ease of use and attitude toward behavior, explains customer behavior. Therefore, the following hypothesis is formulated:

H5: Perceived ease of use positively influences customers' attitude toward AI chatbot

4.4.6. Perceived Usefulness and Attitude (H6)

Several studies have assessed the impact of perceived usefulness on customers' attitudes toward chatbots. For example, Soares, Camacho, and Elmashhara (2022) found significant positive effects of perceived usefulness on attitudes toward using chatbots as digital assistants in e-commerce sites. They argued that customers are more likely to develop an affective attitude toward the chatbot service if they perceive it as more valuable. Similarly, Kasilingam (2020) also found that customer use of shopping chatbots for shopping strongly impacts perceived usefulness and their attitude. They believe that good, valuable chatbots can satisfy their demands and needs. Furthermore, Dharwadkar and Deshpande (2018) learned that in medical health chatbots, perceived usefulness was significantly predictive of people's affective attitude to contribute to lowering barriers by facilitating access to information and reducing the risk of stigmatization. We, therefore, propose the following hypothesis:

H6: Perceived usefulness positively influences customers' attitude toward AI chatbot

4.4.7 Attitude and Customer-Brand Relationship (Satisfaction, Brand Trust, Commitment)

Sheeran and Orbell (1999) found that compared with intentions, the consequences of actions (attitudes) are more likely to predict behavior. Similarly, Friese, Hofmann, and Wänke (2008) studied customer behavior and found that attitudes are valuable in predicting customers’ behavior. In this study, attitude has been considered an essential variable in bridging the technology adoption and customer-brand relationship this research, especially for the second stage of affective attitude. Nguyen, Quach, and Thaichon (2022) said customers' attitude toward the AI chatbot easily influences customer-brand relationships in the hotel industry. They reasoned that many hotels used AI technology to increase efficiency and satisfy their customers' attitudes. During this process, customers are willing to build relationships with AI chatbots in the hotel industry (Bozbay et al., 2018).

Existing research suggests that customers with a positive attitude toward a company are more likely to be satisfied, feel more loyal, and trust (Danniswara et al., 2020). Jin and Youn (2023) found that affective attitude influences brand satisfaction toward the AI chatbot. Han et al. (2018) examined the affective attitude contributing to how people feel about a chatbot. They found that a positive hedonic experience is crucial to forming an attitude, affecting brand satisfaction, trust, and commitment. According to Bergner et al. (2023), when applied to a branded chatbot, the attitude as an emotional response to the shopping experience shows a significant relationship with long-term brand commitment. They advocated that making consistent efforts towards developing a satisfying experience is the outcome of customer attitude. Similarly, good customer attitudes regarding firms and brands have long been linked to business results such as higher revenue and customer satisfaction (Trang et al., 2019). As a result, many firms will aim to enhance customers' favorable attitudes toward their brands to increase customer satisfaction (Kim et al., 2016). Besides, Danniswara et al. (2020) also analyzed the effects of attitudes on social media, and they found that their attitudes influenced consumers' trust in brands and their commitment. We, therefore, propose the following hypotheses:

H7a: Customers' attitude positively influences satisfaction
H7b: Customers' attitude positively influences brand trust
H7c: Customers' attitude positively influences commitment

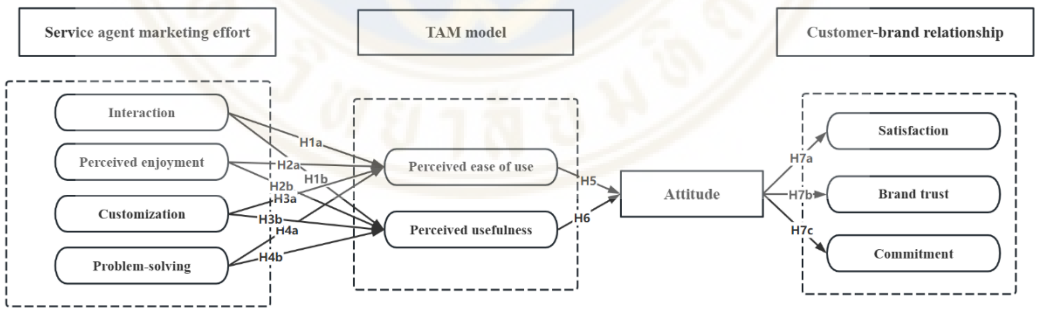

Figure 4.1 The proposed hypotheses of the AI chatbot.

4.5 Research design

4.5.1 Measurement

To quantitatively analyze the impact of AI chatbots on customer-brand relationships, this study developed a structured questionnaire based on constructs identified during the qualitative phase. Each construct was measured using established scales adapted to the context of AI chatbot interactions, ensuring validity and reliability. The quantitative analysis enables researchers to measure the characteristics of the chatbot in achieving its objectives, such as answering user queries or completing tasks by using English questionnaires. The amount of data on user interaction provides researchers valuable insights into the chatbot's performance and helps researchers test the relationship between customers and the chatbot's brand.

The researchers adapted the questions from these researchers (Alharbi, 2020; Chung et al., 2020; Cheng & Jiang, 2021a) to form the questionnaire. The researchers also slightly modify the questionnaire as it becomes more suitable for this study. Then, the researchers conducted a pilot test. Burns and Bush (2005) defined the analysis pilot test as a questionnaire conducted on a symbolic group of small-scale respondents, so it is convenient to show that the questionnaire is incorrect before starting the survey. Items were assessed on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), capturing the degree to which participants agreed with each statement. The researchers collected valid responses from 50 participants. The target population for this research comprises Chinese digital consumers who have experience using Alipay AI chatbots. This group was selected based on its frequent engagement with AI-based services and higher likelihood of having formed opinions regarding chatbot interaction and brand relationship. Researchers use statistical tools to test the reliability of each independent variable based on the coefficient alpha. Malhotra (2004) said that when the alpha value was more than 0.7, it had the reliability of satisfaction. According to the results, all constructs demonstrated acceptable to excellent levels of internal consistency, with Cronbach's Alpha values exceeding the minimum threshold of 0.8 in Table 4.3.

Table 4.3 The Pilot Test of Reliability (n=50)

Variables	Cronbach's Alpha	Internal Consistency
Problem- solving	0.858	Excellent
Satisfaction	0.856	Excellent
Attitude	0.853	Excellent
Interaction	0.847	Good
Customization	0.843	Good
Perceived Usefulness	0.836	Good
Brand Trust	0.829	Good
Perceived Ease of Use	0.823	Good
Perceived Enjoyment	0.819	Good
Commitment	0.808	Good

4.5.2 Sampling and Data Collection

The target population for this study consisted of users who have interacted with AI chatbots, particularly those utilizing the AI chatbot in Nanjing, China. Participants were primarily located in Nanjing, China, a digitally advanced city with high penetration of mobile financial technologies such as Alipay. The Alipay chatbot was selected as the focus of this study due to its significant role in AI-driven customer service in China, offering a representative context for studying customer–brand relationships in chatbot. A snowball sampling approach was employed, focusing on capturing a representative sample of individuals who met the criteria for the study. Snowball sampling expanded the reach well beyond the original sample. However, since the total number of individuals who received the link via peer forwarding is unknown, an accurate response rate cannot be calculated. This is a common limitation of online snowball sampling (Baltar & Brunet, 2012; Naderifar et al., 2017), but it remains a valid and widely accepted approach for accessing niche or hard-to-reach populations in exploratory or behavioral technology research (Bryman, 2016). Considering the user population of AI chatbots in Nanjing, China, conducting a thorough quantitative analysis is imperative. An integral facet of this analysis entails establishing an optimal sample size for data collection, facilitating robust conclusions regarding the chatbot's performance. The researchers intend to employ well-established formulas for determining sample size, as Cohen (1988) and Westland (2010) proposed. The formula systematically incorporates critical parameters, including anticipated effect size, desired statistical power level, number of latent and observed variables, and probability level. By adhering to this methodological framework, the research endeavors to ensure statistical rigor in its quantitative analysis, contributing to the reliability and validity of the findings. The formula for calculating sample size is given as follows:

n=max(n1, n2)

$$n_1 = \left\lceil 50\left(\frac{j}{k}\right)^2 - 450\left(\frac{j}{k}\right) + 1100 \right\rceil$$

$$n_2 = \left\lceil \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left(A\left(\frac{\pi}{6} - B + D\right) + H\right)^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2B - C - 2D\right)} \right) \right\rceil$$

$$A = 1 - \rho^2$$

$$B = \rho arcsin\left(\frac{\rho}{2}\right)$$

$$C = \rho arcsin(\rho)$$

$$D = \frac{A}{\sqrt{3 - A}}$$

$$H = \left(\frac{\delta}{z_{1-\frac{\alpha}{2}} - z_{1-\beta}}\right)^2$$

where: *j*= the number of observed variables

k=the number of latent variables

ρ=estimated Gini correlation for a bivariate normal random vector

δ= anticipated effect size

α=Sidak-corrected Type I error rate

β= Type II error rate

z = A standard normal score

To accurately determine the sample size for evaluating the AI chatbot, it is crucial to select the values for the effect size carefully, desired statistical power level, and probability level. Serdar et al. (2021) found that the large effect size would influence the independent variables on the dependent variables. Thus, the more significant the effect size for the research, the more practical significance of the research outcome. Besides, the appropriate values for these parameters can vary depending on the specific goals of the analysis and the characteristics of the chatbot's performance metrics. Thus, the researchers set the anticipated effect size to be 0.3, the desired statistical power level to be 0.8, and the probability level to be 0.05. After the calculation, the researchers found that the recommended sample size was at least 256.

Data collection was conducted through an online survey (Wenjuanxing) designed to measure several dimensions of user interaction with the AI chatbot, including perceived usefulness, ease of use, trust, enjoyment, customization, and problem-solving capabilities. The link was distributed via WeChat. The survey included closed-ended questions based on established measurement scales to quantify participants' attitudes toward the chatbot and its impact on the customer-brand relationship. The researchers collected 332 valid responses after deleting some invalid and incomplete data. Table 4.4 shows the profiles of the respondents.

4.5.3. Data Analysis and Results

Then, the researchers use quantitative methods to analyze the survey data and test the hypotheses outlined in the conceptual framework. Structural Equation Modeling (SEM) was the primary analytical technique to examine the relationship between variables. The analysis focused on understanding how these features influenced users' perceptions of ease of use and usefulness, ultimately shaping their attitudes toward the chatbot and fostering customer-brand relationships.

Table 4.4 Demographic information (n=332)

Items	Category	Frequency	Percentage
Gender	Male	170	51.2%
	Female	162	48.8%
Age	20 or less	34	10.24%
	21-30	114	34.34%
	31-40	103	31.02%
	31-50	68	20.48%
	Above 50	13	3.92%
Gross Annual Income (CNY)	50,000 or less	53	15.96%
	50,001 to 100,000	144	43.37%
	100,001 to 150,000	96	28.92%
	150,001 to 200,000	28	8.43%
	200,001 or more	11	3.31%
Education Level	High school or below	30	9.04%

Items	Category	Frequency	Percentage
	Bachelor	23	6.93%
	Master	199	59.94%
	PhD.	59	17.77%
	Other	21	6.33%
Employment Category	Management	31	9.34%
	Student	34	10.24%
	Government	15	4.52%
	Employee	198	59.64%
	Self-employee	51	15.36%
	Other	3	0.9%

Table 4.4 provides demographic information about the respondents, which includes gender, age, gross annual income, education level, and employment category. The sample consists of 51.2% male and 48.8% female respondents. The age distribution is pre-dominantly between 21-40 years (65.36%), while 43.37% of the respondents earn between CNY 50,001 to 100,000 annually. Most participants hold a master's degree (59.94%) and are employees (59.64%). This diverse demographic representation ensures a comprehensive understanding of the attitudes toward the AI chatbot.

4.5.4 Exploratory factor analysis (EFA)

The EFA analyzes data patterns, identifies correlations, and condenses data according to item loadings (Hair et al., 2021). It organizes the variables for subsequent analysis with tools such as CFA and SEM. Factor analysis and reliability testing are conducted for the factors. Table 4.5 presents the KMO measure of sample adequacy and Bartlett's test of sphericity for the entire component.

Table 4.5 KMO and Bartlett's Test

Kaiser-Meyer-Olkin		0.902
	Approx.Chi-Square	6564.213
Bartlett's Test of Sphericity	Df	780
	Sig.	<0.001

Exploratory Factor Analysis was conducted to identify underlying relationships among the variables. The Kaiser-Meyer-Olkin (KMO) measure of sample adequacy is 0.902, indicating that the data is suitable for factor analysis. Bartlett's Test of Sphericity is significant (Chi-Square = 6564.213, df = 780, $p < 0.001$), confirming that item correlations are adequate for factor analysis.

Table 4.6 Rotated Component Matrix

	Component									
	1	2	3	4	5	6	7	8	9	10
PI1	0.628									
PI2	0.811									
PI3	0.798									
PI4	0.721									
PE1		0.691								
PE2		0.810								
PE3		0.810								
PE4		0.725								
CZ1			0.684							
CZ2			0.810							
CZ3			0.783							
CZ4			0.690							
PS1				0.668						
PS2				0.701						
PS3				0.788						
PS4				0.770						
PEOU1					0.790					
PEOU2					0.711					
PEOU3					0.811					
PEOU4					0.698					
PU1						0.804				
PU2						0.700				
PU3						0.713				
PU4						0.818				
ATT1							0.796			
ATT2							0.748			
ATT3							0.734			
ATT4							0.617			
SA1								0.759		
SA2								0.766		
SA3								0.805		
SA4								0.773		
BT1									0.709	
BT2									0.688	
BT3									0.829	
BT4									0.775	
CO1										0.754
CO2										0.705
CO3										0.700

Component										
	1	2	3	4	5	6	7	8	9	10
CO4										0.771

Note: Extraction Method: Exploratory Factor Analysis

Table 4.6 presents the rotated component matrix. Ten components were extracted, with high factor loadings indicating strong relationships between variables and their respective components to support the validity of the constructs used in this study. The factors include interaction, enjoyment, customization, problem-solving, ease of use, usefulness, attitude, brand satisfaction, trust, and commitment.

4.5.5 Confirmatory factor analysis (CFA)

Exploratory Factor Analysis (EFA) was employed in this study not for exploring or identifying new constructs, but to statistically validate the underlying structure of the measurement items adapted from prior literature. While the theoretical grouping of items was conceptually pre-established, EFA served to confirm whether the empirical data supported this structure. Specifically, EFA was used to assess the convergent and discriminant validity of the items and ensure that each item loaded significantly on its respective factor with minimal cross-loadings. Table 4.7 shows the Convergent validity and reliability analysis.

Table 4.7 Convergent validity and reliability analysis

Constructs	**Items**	**Factor Loading**	**Mean**	**AVE**	**Cronbach's Alpha**
Perceived Interaction (PI)	PI1	0.720	3.810	0.568	0.838
	PI2	0.832	3.870		
	PI3	0.750	3.916		
	PI4	0.705	3.837		
Perceived Enjoyment (PE)	PE1	0.761	3.717	0.594	0.851
	PE2	0.777	3.651		
	PE3	0.819	3.648		
	PE4	0.714	3.633		
Customization (CZ)	CZ1	0.740	3.870	0.553	0.830
	CZ2	0.750	3.858		
	CZ3	0.766	3.843		
	CZ4	0.711	3.880		
Problem-solving (PS)	PS1	0.762	3.735	0.559	0.835
	PS2	0.695	3.702		
	PS3	0.763	3.723		
	PS4	0.767	3.786		
Perceived Ease of Use	PEOU1	0.790	3.578	0.596	0.855

Constructs	**Items**	**Factor Loading**	**Mean**	**AVE**	**Cronbach's Alpha**
(PEOU)	PEOU2	0.753	3.608		
	PEOU3	0.782	3.554		
	PEOU4	0.761	3.584		
Perceived Usefulness (PU)	PU1	0.764	3.813	0.591	0.852
	PU2	0.742	3.720		
	PU3	0.762	3.762		
	PU4	0.803	3.771		
Attitude (ATT)	ATT1	0.777	3.792	0.546	0.826
	ATT2	0.780	3.801		
	ATT3	0.712	3.825		
	ATT4	0.679	3.804		
Satisfaction (SA)	SA1	0.774	3.566	0.613	0.863
	SA2	0.754	3.569		
	SA3	0.815	3.602		
	SA4	0.788	3.479		
Brand Trust (BT)	BT1	0.681	3.795	0.572	0.840
	BT2	0.756	3.771		
	BT3	0.805	3.762		
	BT4	0.772	3.807		
Commitment (CO)	CO1	0.749	3.886	0.549	0.829
	CO2	0.745	3.843		
	CO3	0.734	3.870		
	CO4	0.705	3.877		

Table 4.7 presents the Confirmatory Factor Analysis (CFA) results, demonstrating that all measured constructs—such as Perceived Interaction (PI), Perceived Enjoyment (PE), Customization (CZ), Problem-solving (PS), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU)—exhibit high reliability and validity. The Average Variance Extracted (AVE) values for each construct surpass the threshold of 0.5, confirming convergent validity, while Cronbach's alpha values are all above 0.8, indicating robust internal consistency. The high factor loadings for each item (above 0.7) further affirm the reliability of each construct in accurately measuring intended characteristics. These reliability metrics ensure that constructs like Satisfaction (SA), Brand Trust (BT), and Commitment (CO) are robust, capturing respondents' perceptions consistently.

Table 4.8 The correlation matrix

Constructs	PI	PE	CZ	PS	PEOU	PU	ATT	SA	BT	CO
PI	**0.754**									
PE	0.269	**0.771**								
CZ	0.322	0.324	**0.730**							
PS	0.335	0.401	0.331	**0.748**						
PEOU	0.430	0.399	0.431	0.404	**0.772**					
PU	0.315	0.382	0.379	0.366	0.384	**0.769**				
ATT	0.402	0.316	0.347	0.324	0.353	0.372	**0.739**			
SA	0.357	0.325	0.265	0.289	0.312	0.330	0.367	**0.783**		
BT	0.244	0.357	0.314	0.350	0.408	0.311	0.401	0.306	**0.756**	
CO	0.251	0.358	0.281	0.407	0.408	0.373	0.402	0.338	0.329	**0.741**

Note: The square root of AVE for each latent construct is given in diagonals.

The correlation matrix in Table 4.8 demonstrates significant positive relationships among all constructs, with diagonal values representing the square root of AVE for each latent construct. These diagonal values exceed the inter-construct correlations, satisfying the requirement for discriminant validity. Constructs such as Perceived Ease of Use, Perceived Enjoyment, Customization, and Problem-solving positively correlate with Attitude, Brand Satisfaction, Brand Trust, and Brand Commitment, supporting the study's hypothesis that these characteristics significantly influence user attitudes and brand relationship outcomes.

Table 4.9 'Goodness-of-fit' statistics for the structural model

Model Fit Indicators	Required Values	Model Result	Remarks
'CMIN/DF'	1-3	1.172	Excellent
'RMSEA'	<0.08	0.023	Good
'SRMR'	<0.08	0.037	Good
'GFI'	>0.90	0.895	Acceptable
'CFI'	>0.90	0.980	Excellent
'IFI'	>0.90	0.980	Excellent
'TLI'	>0.90	0.978	Good

Table 4.9 presents the goodness-of-fit statistics for the structural model. The model fit indicators, such as CMIN/DF (1.172), RMSEA (0.023), SRMR (0.037), GFI (0.895), CFI (0.980), IFI (0.980), and TLI (0.978), suggest an excellent fit to the data. However, if the GFI is less than 0.9, Baumgartner and Homburg (1996) suggested that if

the GFI is more than 0.8 but not over 0.9, it also meets the requirement for model fit. For this study, we found that GFI is 0.895. The values are within the acceptable range, confirming that the hypothesized model fits well with the observed data.

4.5.6 Structural Equation Modelling

The SEM results in Figure 4.2 indicate that perceived ease of use and perceived usefulness significantly influence customer attitudes toward the AI chatbot, which, in turn, positively affects brand satisfaction, trust, and commitment. The positive relationships between the constructs highlight the importance of chatbot characteristics, such as interaction, perceived enjoyment, customization, and problem-solving, in shaping customer perceptions and enhancing brand relationships. The results demonstrate that AI chatbot characteristics significantly impact customer perceptions, ultimately influencing customer attitudes and brand relationships. Enhancing features like interaction, customization, and problem-solving can lead to better customer attitude, increased satisfaction, trust, and long-term brand commitment.

Table 4.10 The result of R^2

Endogenous construct	R^2 Value	Interpretation
Perceived ease of use	0.350	Moderate
Perceived usefulness	0.264	Weak to Moderate
Attitude	0.191	Weak
Satisfaction	0.135	Weak
Brand trust	0.161	Weak
Commitment	0.162	Weak

The R^2 values presented in the structural model indicate varying levels of explanatory power across the endogenous constructs. Perceived ease of use has an R^2 value of 0.350, suggesting a moderate level of variance explained by its predictors. Perceived usefulness, with an R^2 of 0.264, falls into the weak-to-moderate range. Attitude, satisfaction, brand trust, and commitment all exhibit R^2 values below 0.20, indicating relatively weak explanatory power. While these values are not high, they are acceptable within behavioral research, where psychological and experiential variables often contribute to modest levels of explained variance. The results imply that while the model effectively captures some key influences on user perceptions and brand-related outcome.

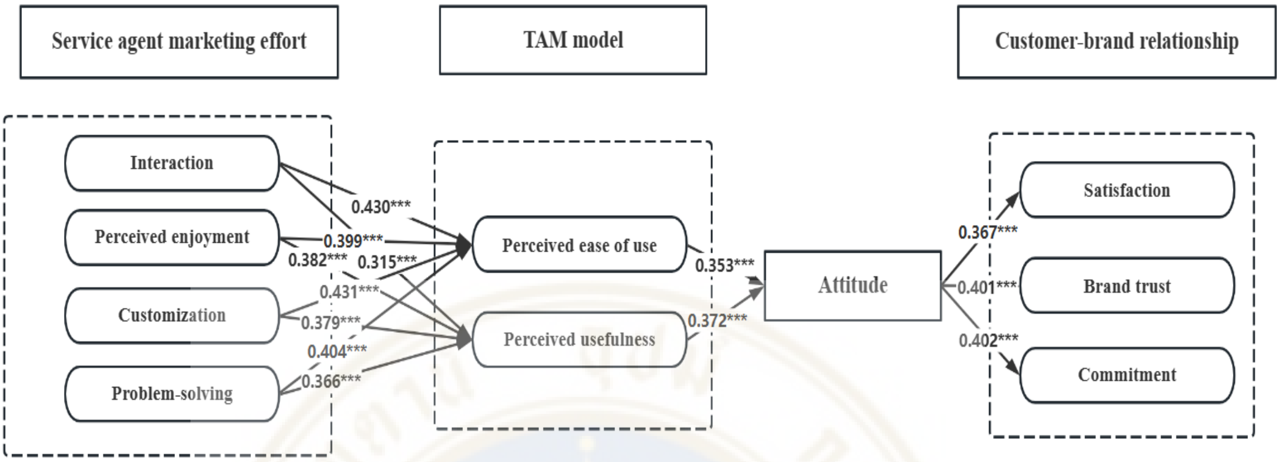

Figure 4.2 Modeling Results

(*Note: *** means significant at the p < 0.001 level*)

4.5.7 Indirect Effect and Mediation Analysis

Table 4.11 The result of mediation analysis

					95% Confidence interval	
	Estimate	**Std.Error**	**z-value**	**P**	**Lower**	**Upper**
PEOU—ATT-- SAT	0.064	0.020	3.221	0.001	0.025	0.103
PU—ATT—SAT	0.075	0.022	3.399	<.001	0.032	0.118
PEOU—ATT—BT	0.061	0.018	3.396	<.001	0.026	0.096
PU—ATT—BT	0.071	0.020	3.607	<.001	0.032	0.110
PEOU—ATT—CO	0.054	0.016	3.290	0.001	0.022	0.086
PU—ATT—CO	0.063	0.018	3.480	<.001	0.027	0.098

Note: Delta method standard errors, normal theory confidence intervals, ML estimator

The mediation analysis revealed in Table 4.11 that attitude plays a significant mediating role in the relationships between perceived ease of use and perceived usefulness with all three customer–brand relationship outcomes: satisfaction, brand trust, and commitment. Specifically, the indirect effects from both TAM variables to the relational outcomes via attitude were statistically significant at the $p < .001$ level, with confidence intervals that did not include zero. For example, perceived usefulness showed an indirect effect on satisfaction ($\beta = 0.075$), brand trust ($\beta = 0.071$), and commitment ($\beta = 0.063$), while perceived ease of use demonstrated similar significant pathways. These results confirm that attitude serves as a psychological mechanism through which users' evaluations of the chatbot influence their relationship with the brand, supporting the proposed cognitive–affective–behavioral pathway in the model.

4.6 Discussions and Implications

This study focuses on AI chatbots' significant role in influencing customer-brand relationships. The study indicates that the key characteristics of AI chatbots, such as perceived interaction, enjoyment, customization, and problem-solving capabilities, positively affect users' perceived ease of use and usefulness. These perceptions, in turn, shape customer attitudes toward the AI chatbot, which subsequently impacts brand satisfaction, trust, and commitment. In this section, the researchers discuss the findings related to our research objectives. Then, we highlight the implications for the theoretical and managerial contributions. Last, we conclude the study and address the limitations and future study.

4.6.1 Discussions

The qualitative phase of this study, conducted through semi-structured interviews with 20 Chinese users of the Alipay AI chatbot, provided rich, exploratory insights into user perceptions and preferences when interacting with AI-driven customer service. Thematic analysis of the interview transcripts revealed four core themes that align with established constructs in the technology adoption literature, as well as several emergent themes that point to additional affective and contextual dimensions of user experience. Participants consistently highlighted the importance of the chatbot's ability to respond quickly, understand user input, and maintain a natural flow of conversation. Successful interactions were those that felt human-like or intuitive, while failed interactions often stemmed from misunderstanding commands or inflexible scripted replies. Some users described using the chatbot as enjoyable or even fun, especially when the tone was friendly or humorous. Others appreciated the reduction in frustration compared to waiting for human agents. Many participants valued the chatbot's ability to tailor responses based on personal history or preferences—such as remembering payment settings or offering shortcuts for frequent queries. Participants viewed the chatbot's core value in its ability to resolve tasks efficiently—whether checking account balances, resetting passwords, or resolving transaction disputes. The quantitative analysis shows that perceived ease of use and usefulness are critical determinants of customer attitudes toward chatbots, consistent with the Technology Acceptance Model (TAM). This implies that users are more likely to adopt and have a favorable attitude toward intuitive chatbots that offer tangible benefits. Moreover, the findings suggest that while interaction is essential for enhancing perceived ease of use, the chatbot's ability to handle complex, emotionally nuanced problems is limited. This limitation affects perceived usefulness, particularly for tasks that require empathy or detailed understanding. The study's findings on problem-solving capabilities reveal that AI chatbots are adequate for fundamental issues but are less successful in addressing complex inquiries, which may hinder their perceived usefulness in specific contexts. Joksimovic et al. (2023) also support the idea that problem-solving is one of the most important functions in AI chatbot services. The more effective the AI chatbot is in handling the problems, the more customers intend to use the AI chatbot.

Regarding customer-brand relationship outcomes, the study found that a positive attitude toward the AI chatbot significantly contributes to customer satisfaction, trust, and commitment. Satisfaction with the chatbot is derived from its efficiency in handling routine tasks, while trust is more conditional, depending on the context and the complexity of user needs. Commitment to the long-term use of AI chatbots is contingent on the technology's ability to evolve, particularly in areas such as empathy and contextual understanding.

4.6.2 Theoretical implications

This study provides significant theoretical insights by extending existing technology acceptance models and customer-brand relationships within the context of

AI chatbots. By examining the impact of AI chatbot features on customer satisfaction, trust, and commitment, the study offers a nuanced understanding of how digital agents function as interactive representatives of brands. These findings contribute to several theoretical frameworks, including the Technology Acceptance Model (TAM), the Cognitive-Affective-Behavior (CAB) Model, and theories related to customer-brand relationships.

Firstly, this research integrates dimensions like interaction, perceived enjoyment, customization, and problem-solving as external factors to influence the TAM, extending the model's applicability to AI-enabled customer service contexts. By highlighting the importance of the characteristics of AI chatbots through enjoyable interactions and customized responses, this study suggests that AI chatbots must go beyond functional utility and foster a more personalized and pleasant experience to strengthen customer usage.

Secondly, this research validates TAM's core constructs by demonstrating that Perceived Ease of Use and Perceived Usefulness are still critical determinants of chatbot acceptance. Users are more likely to adopt and engage with chatbots that they find easy to use and beneficial in achieving their goals, such as obtaining quick responses, resolving simple issues, or accessing personalized information. The research finds that chatbots with user-friendly designs contribute positively to customer attitude, supporting TAM's assertion that ease of use facilitates acceptance. Similarly, Perceived Usefulness was measured by the chatbot's ability to enhance efficiency and productivity. Chatbots that effectively handle repetitive tasks, answer frequently asked questions, and streamline processes are perceived as highly useful. This study confirms that when users recognize a chatbot's usefulness, they are more inclined to rely on it, reinforcing TAM's premise that perceived utility is a key motivator for technology adoption.

The study reinforces the Cognitive-Affective-Behavior Model by showing that cognitive perceptions (ease of use, usefulness) influence affective attitudes and subsequent behavioral outcomes (satisfaction, brand trust, commitment). This implies that customer attitudes toward AI chatbots can be important in forming lasting customer-brand relationships. The study suggests that brands can enhance customer relationships by designing chatbots that elicit positive affective responses. The theoretical contribution here is the expansion of TAM and the Cognitive-Affective-Behavior Model, emphasizing that digital engagement tools like chatbots must focus on cognitive and affective factors to drive positive user attitudes and behaviors.

Lastly, this study contributes to the literature on customer-brand relationships by examining AI chatbots as digital agents influencing key aspects of satisfaction, brand trust, and commitment. As digital brand representatives, AI chatbots influence critical aspects of the customer-brand relationship. In traditional customer-brand relationships, direct human interactions are pivotal in establishing trust, satisfaction, and loyalty. However, with the growing adoption of AI in customer service, brands increasingly rely on chatbots to engage with customers and foster long-term relationships. This research offers insights into how satisfaction, brand trust, and commitment affect customers' behavior.

4.6.3 Managerial implications

From a managerial perspective, this research highlights actionable strategies for organizations seeking to leverage AI chatbots to enhance customer-brand relationships.

On the one hand, interaction is one of the most critical factors in AI chatbot success, especially in customer service. Managers should prioritize designing chatbots that deliver consistent and timely responses to common inquiries. Customers expect immediate assistance, and any delay or lack of responsiveness can lead to frustration and damage the brand's reputation. Therefore, chatbots must be optimized for speed, ensuring users experience seamless and efficient interaction. Managers should consider investing in advanced natural language processing (NLP) and sentiment analysis to enable chatbots to respond with emotional intelligence. By enhancing the chatbot's ability to detect and respond to emotional cues, companies can provide a more satisfying and supportive experience, especially valuable in customer service contexts. Customization is another crucial area. Chatbots adapting to individual user preferences and responding to specific professional or personal needs can provide a more relevant and satisfying experience. Businesses can leverage data analytics to personalize chatbot interactions, enhancing perceived usefulness and fostering a stronger connection between the customer and the brand. Companies should invest in advanced natural language processing (NLP) and machine learning technologies to make chatbots more adaptive and responsive, thereby increasing customer relationships. Continuous improvement through machine learning is vital for enhancing a chatbot's problem-solving capabilities over time. Managers should implement feedback loops that allow the chatbot to learn from each interaction and refine its responses. By analyzing past interactions and identifying patterns in customer inquiries, chatbots can become more adept at predicting and addressing user needs. This iterative learning process demonstrates the brand's commitment to evolving its customer support capabilities and positions the chatbot as a reliable problem-solving tool.

Conversely, TAM's constructs of perceived ease of use and perceived usefulness remain pivotal for driving chatbot adoption, providing actionable insights for managers to simplify interfaces, streamline customer interactions, and demonstrate the chatbot's value in enhancing efficiency. Managers can incorporate enjoyable and human-like qualities into chatbot interactions, such as humor, empathy, or gamification, to make the experience more engaging while ensuring personalized responses that cater to individual user needs. Customer attitudes and customer-brand relationships further contribute to actionable strategies for fostering satisfaction, brand trust, and commitment. Positive attitudes can be cultivated through chatbots that consistently deliver accurate, timely, and empathetic responses, addressing functional and emotional customer needs. Managers can strengthen customer-brand relationships by aligning chatbot features with TAM principles and relational goals, positioning chatbots as critical tools for fostering loyalty and competitive differentiation in digital customer service.

4.6.4 Limitations and future study

This study has some limitations that drive the future study. First, future research could explore the role of AI chatbots in industries beyond customer service, such as healthcare, education, and entertainment. Examining how chatbots meet the unique needs of different sectors would provide a more comprehensive understanding of their capabilities and limitations. Second, cultural and demographic factors significantly shape customer perceptions, attitudes, and behaviors toward AI chatbots. Despite the global application of chatbots across industries, this study does not profoundly explore how cultural norms, values, and demographic diversity influence user acceptance and satisfaction. Future research could provide nuanced insights into tailoring chatbot design and interactions for specific audiences. Third, the study is the geographic concentration of the sample, which was drawn exclusively from Nanjing, China—a highly urbanized and digitally advanced city. While this location provides a relevant context for studying AI chatbot adoption within China's leading super app ecosystem (i.e., Alipay), the findings may reflect culturally specific behaviors and expectations that do not fully generalize to other regions or user populations. Cultural norms regarding trust in technology, digital service expectations, and customer–brand engagement may vary significantly across areas in China. Therefore, while the present study contributes novel insights into AI-driven customer experience in Nanjing, China, future research should pursue cross-cultural validation to examine whether the proposed model holds in different areas of China. Last, AI chatbots in customer-brand relationships should explore the role of customer experience as an additional variable. While this study has highlighted the impact of interaction, customization, perceived enjoyment, and problem-solving on customer satisfaction, trust, and commitment, customer experience could provide deeper insights into how users emotionally and cognitively perceive their interaction with AI chatbots. By examining customer experience, researchers can understand chatbot's impact on customer-brand relationships.

4.7 Conclusions

AI chatbots have become an integral part of modern customer service, and this study provides empirical evidence on how their characteristics influence customer perceptions and their broader impact on customer-brand relationships. Using a mixed-method approach, the research integrates insights from the E-service agent effort framework, the Technology Acceptance Model (TAM), the Cognitive-Affective-Behavior (CAB) model, and customer-brand relationship theories. The findings highlight that interaction, perceived enjoyment, customization, and problem-solving abilities are key predictors of customers' perceptions of AI chatbots.

These perceptions positively shape customers' attitudes toward chatbots, enhancing brand satisfaction, trust, and commitment—essential for building strong and lasting customer-brand relationships.

CHAPTER V
IMPLICATIONS AND CONCLUSIONS

This chapter synthesizes the findings of the study and discusses their theoretical and practical implications in light of the research questions and objectives introduced in Chapter 1. The aim of this dissertation was to examine how AI chatbot design features—such as interaction, perceived enjoyment, customization, and problem-solving—shape user perceptions and influence customer–brand relationship outcomes in the context of digital service experiences. Grounded in the Technology Acceptance Model (TAM), the study proposed an integrated framework to understand how cognitive and affective evaluations of AI chatbot interactions contribute to attitudinal and relational outcomes, such as satisfaction, brand trust, and commitment.

By linking the qualitative exploration, conceptual development, and empirical validation across Chapters 2 through 4, this chapter presents a cohesive reflection on the overall research. It highlights how the findings contribute to extending existing theories, refining measurement constructs, and informing future digital service strategies. Chapter 5 underscores the study's contribution to the broader understanding of AI-chatbot service experiences and their role in fostering meaningful customer-brand relationship.

5.1 Implications

This study contributes to theory by integrating and extending the Technology Acceptance Model (TAM) and relationship marketing theory in the context of AI chatbot adoption in China's e-service sector. While previous literature has applied TAM primarily to predict user acceptance of digital tools, this research expands the framework by incorporating customer–brand relationship (CBR) variables—such as satisfaction, trust, and commitment—as outcomes of users' interaction with AI-enabled service agents. Importantly, this dissertation positions attitude as a mediating construct that connects cognitive perceptions of chatbot features (e.g., ease of use, usefulness) with relational outcomes, offering a conceptual bridge between the technology and branding domains. The study responds to recent calls for more integrated models that capture the affective and relational dimensions of technology-mediated service experiences.

5.1.1 Extension of Technology Acceptance Model (TAM) in AI Chatbot Research

This study provides significant contributions to the theoretical domain by extending the Technology Acceptance Model (TAM) and integrating it with chatbot-specific attributes. Traditional TAM focuses on perceived ease of use and perceived usefulness as determinants of technology adoption. However, this research incorporates additional chatbot characteristics such as interaction, perceived enjoyment, customization, and problem-solving capabilities. These elements influence customer perceptions and attitudes, demonstrating that AI chatbots are not merely digital assistants but integral components of brand engagement. Future studies should explore how these attributes interact dynamically in various industries, such as healthcare, finance, and retail, to enhance our understanding of chatbot efficacy across different customer touchpoints.

5.1.2 The Role of AI Chatbots in the Affective-Behavioral Model

By integrating the A-B-C (Affective-Behavioral-Cognitive) model, this research highlights how AI chatbot interactions influence customer emotions and behavior intention. Besides, attitude is not merely as a direct outcome of perceived ease of use and usefulness, but as a pivotal mediator that channels cognitive evaluations into relational outcomes such as trust and commitment. The study contributes to an integrated framework that links user–technology interaction with brand-level relational constructs, advancing the underdeveloped intersection between service technology adoption and relationship marketing. Brand relationships have been studied through human interactions. However, this study demonstrates that AI chatbots can elicit emotional engagement, thereby shaping customer attitudes toward the brand. This insight challenges the conventional view that human interaction is the primary driver of brand relationships. The research fills a gap by empirically validating that AI-driven interactions can create meaningful emotional and behavioral responses, which have been underexplored in prior literature. Future research should further investigate the long-term psychological effects of AI chatbot interactions on brand loyalty and customer retention.

5.1.3 Bridging Digital Engagement and Brand Commitment

The findings suggest that AI chatbots are crucial in fostering brand trust, satisfaction, and commitment, thus strengthening customer-brand relationships. The study contributes to brand management literature by illustrating how AI-driven digital touchpoints serve as brand representatives, maintaining consistency in communication and delivering personalized experiences. This expands the scope of research on digital engagement and customer experience, encouraging scholars to explore novel constructs such as AI-driven brand advocacy and AI-induced customer loyalty. Previous research has largely focused on AI chatbots in transactional contexts, whereas this study fills a gap by exploring their role in emotional and relational brand-building strategies.

5.1.4 Contributions on Stakeholders

This study offers practical implications for multiple stakeholders in the chatbot business ecosystem. For AI chatbot developers, the findings highlight the importance of enhancing features such as perceived intelligence, customization, and problem-solving capability, which strongly shape users' attitudes and brand perceptions. For customer experience managers, understanding the mediating role of attitude can guide the design of more engaging, user-centric conversational flows that lead to stronger brand commitment. Additionally, platform owners and brand strategists operating within multifunctional environments (such as Alipay) can leverage chatbot interactions as a critical touchpoint to foster trust and satisfaction. While the absence of behavioral usage data (e.g., usage frequency, service type) limits the granularity of recommendations, the conceptual relationships established here offer actionable insights into how user perception drives customer–brand outcomes in AI-mediated service environments.

5.2 Conclusions

This dissertation investigates the role of AI chatbots as e-service agents in developing customer-brand relationships, providing a comprehensive exploration of their intellectual foundation, conceptualization, and empirical validation. The research is structured into three key chapters, each addressing a different but interrelated aspect of AI chatbot applications. Chapter II presents a bibliometric analysis of AI chatbot literature, tracing its intellectual evolution. Chapter III conceptualizes AI chatbots within the Technology Acceptance Model (TAM) framework to understand their role in influencing customer attitudes and brand relationships. Finally, Chapter IV empirically explores how AI chatbot features contribute to digital brand engagement and long-term customer loyalty. The insights from these chapters collectively contribute to advancing knowledge on AI chatbots' strategic role in modern customer-brand interactions.

Chapter II conducts a bibliometric review, providing a structured analysis of the intellectual landscape surrounding AI chatbots. The study compiles data from 571 peer-reviewed articles published between 2005 and 2022, offering insights into the research trends, key authors, influential papers, and conceptual frameworks shaping this field. The bibliometric analysis identifies the most cited studies, highlighting how research on AI chatbots has evolved across disciplines such as computer science, digital health, and marketing. One contribution is mapping the AI chatbot knowledge base through co-citation analysis. The research distinguishes three dominant academic clusters: computer science, which explores the technical advancements in AI chatbots; chatbot service applications, which examine their role in enhancing customer experiences; and digital health, where AI-driven conversational agents are deployed in telemedicine and healthcare management. The study finds that the field has witnessed exponential growth, with the highest concentration of publications emerging in recent years, particularly in journals focused on human-computer interaction, business research, and electronic markets. Moreover, it assesses the geographical distribution of chatbot research, revealing that the United States, China, and India lead in AI chatbot scholarship. These findings underscore the increasing global interest in AI chatbots and their potential for transforming various industries. Moreover, the analysis of citation patterns confirms that AI chatbots are not just a technological trend but an evolving field of study with significant implications for digital customer engagement. The bibliometric review provides a foundation for the subsequent conceptual and empirical investigations by illustrating how AI chatbot research has developed and its future trajectory.

Building on the insights from the bibliometric analysis, Chapter III develops a conceptual framework that positions AI chatbots as e-service agents capable of shaping customer-brand relationships. This chapter applies the Technology Acceptance Model (TAM) as a theoretical lens to explore how AI chatbot characteristics influence customer attitudes. The conceptual model integrates chatbot-specific attributes, including interaction quality, perceived enjoyment, customization, and problem-solving capabilities, as external factors impacting customers' perceptions of chatbot ease of use and usefulness. AI chatbots are pivotal in influencing customer perceptions, emotions, and behaviors. Customers who perceive chatbots as interactive, enjoyable, and capable of addressing their needs tend to develop positive attitudes toward the chatbot and the associated brand. This, in turn, fosters trust, satisfaction, and long-term brand commitment. By incorporating the A-B-C model of attitudes—which consists of cognitive (thinking), affective (feeling), and behavioral (doing) components—the study illustrates how chatbot interactions shape customer attitudes and behavioral intentions toward brands. AI chatbots serve as digital representatives of brands, influencing how customers perceive the brand's accessibility, responsiveness, and service quality. Through natural language processing, predictive analytics, and machine learning, AI chatbots enhance customer engagement by providing personalized interactions that mimic human-like conversations. These interactions are critical in an era where customers expect instant, seamless digital experiences. The chapter highlights how AI chatbot-driven customization fosters brand intimacy by making customers feel understood and valued, strengthening emotional bonds with brands. The study suggests that chatbot transparency, ethical AI usage, and consistent performance are vital factors in ensuring customer trust and mitigating skepticism about AI-driven customer service. The conceptual model developed in this chapter lays the groundwork for the empirical analysis presented in Chapter IV, where the proposed relationships are tested using real-world data.

Chapter IV extends the theoretical model by empirically examining the impact of AI chatbots on customer engagement, brand trust, and long-term loyalty. This study adopts a mixed-methods approach, beginning with qualitative interviews to identify key engagement factors and then conducting a structured survey to validate these insights quantitatively. The research assesses how AI chatbots contribute to digital brand sustainability by fostering brand trust, satisfaction, and commitment. The empirical analysis confirms that AI chatbot features significantly enhance customer perceptions and brand relationships. Specifically, ease of use and perceived usefulness emerge as primary drivers of positive customer attitudes. Customers who find chatbots intuitive, helpful, and efficient are more likely to engage with the brand and perceive it as customer-centric and technologically advanced. Chatbot-driven personalization and proactive engagement are critical factors in enhancing brand loyalty.

The research further highlights the role of AI-powered automation in optimizing digital customer interactions. AI chatbots reduce reliance on human customer support, streamline responses, and provide 24/7 assistance, enhancing operational efficiency while maintaining high-quality customer experiences. These capabilities align with broader industry trends where businesses leverage AI to improve service scalability and cost-effectiveness. Moreover, the findings reveal that chatbots influence customer satisfaction by providing fast, consistent, and personalized responses. Brands that integrate AI chatbots effectively can enhance digital engagement, reduce churn rates, and increase customer retention. The study underscores the importance of human-AI collaboration, suggesting that while AI chatbots are highly effective in handling routine inquiries, human intervention remains necessary for complex customer issues. This hybrid approach ensures that customer experiences remain personalized, empathetic, and trustworthy. Another crucial insight from Chapter IV is that customers' attitudes toward AI chatbots directly affect their brand perception. Customers who perceive chatbot interactions as seamless and valuable are more likely to associate the brand with innovation, efficiency, and customer-centricity.

In contrast, poor chatbot performance—characterized by miscommunication, lack of personalization, or inaccurate responses—can damage brand reputation and erode customer trust. By integrating sustainability and responsible AI practices, this chapter suggests that AI chatbots contribute to customer-brand relationships and sustainable digital transformation. AI-driven automation reduces resource-intensive human support, aligning with businesses' sustainability goals while enhancing customer experiences.

This dissertation comprehensively explores AI chatbots' role in developing customer-brand relationships, from their intellectual foundation and conceptualization to empirical validation. The findings contribute to theoretical advancements by extending TAM with chatbot-specific attributes and practical implications by offering businesses insights into chatbot-driven customer engagement strategies. The research confirms that AI chatbots enhance customer-brand relationships by improving interactivity, personalization, problem-solving capabilities, and overall customer satisfaction. However, chatbot success depends on user perceptions of trust, ease of use, and usefulness, which can significantly influence brand loyalty. AI chatbots can become powerful tools for long-term brand engagement by fostering trust and providing high-quality digital interactions.

Future research should explore the evolving role of AI in customer-brand interactions, including emotion AI, conversational intelligence, and ethical AI considerations. As AI chatbot technology advances, further studies could examine how AI-driven brand engagement strategies impact consumer decision-making and loyalty over extended periods.

In conclusion, AI chatbots represent a transformative force in digital brand management, offering businesses an innovative approach to customer engagement, relationship-building, and brand loyalty. As AI capabilities evolve, brands that strategically integrate AI chatbots will gain a competitive advantage in delivering seamless, personalized, and meaningful customer experiences.

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APPENDICES

APPENDIX A: Qualitative Questionnaire

Section 1: Overall of the AI chatbot

1. Do you often use the AI chatbot?

2. What do you think about the AI chatbot?

Section 2: the characteristics of AI chatbot

3. Do you think which characteristics AI chatbots should have?

4. Do you think the chatbot has enough knowledge to answer customers' questions? How?

5. How do you feel when you interact with the AI chatbot? Do they give you individual attention?

6. Do you enjoy using the chatbot? Why do you think using a chatbot is enjoyable?

7. Do you think the chatbot can meet your personal needs?

8. Do you think the chatbot provides product information according to your preferences?

9. Is the chatbot interested in helping you to solve the problem?

10. How do you think the chatbot handles the customer complaints?

Section 3: Adoption of technology

11. How do you think the chatbot service is easy to get or use to do what you want?

12. Do you feel easy to use the chatbot?

13. Do you think it will enhance your effectiveness in your job by using the chatbot?

14. Do you trust the chatbot when using the chatbot service?

15. Do you think the chatbot will protect your information?

Section 4: The customers' perception

16. How do you feel when using the chatbot service and not the rather materials?

17. Do you want to use the chatbot service rather than other materials?

18. Do you think you should use the chatbot service?

19. What is your attitude when using the chatbot service?

Section 5: Customer brand relationship

20. Do you like using the brand of chatbot?

21. Do you believe that both the brand of chatbot and you have benefited from the relationship?

22. Do you believe that whenever the brand makes an important decision, you know it will be concerned about you?

23. Do you think you are confident about the chatbot's ability?

24. Can the chatbot maintain a long-term commitment to you?

25. Do you want to maintain a long-term relationship with you?

Thank you for sharing your valuable insights and expertise with us today. It has been a pleasure discussing AI-chatbot as an E-service agent to develop a customer-brand relationship with you. We truly appreciate your time and wish you the best in your future endeavors. Have a great day!

APPENDIX B: Quantitative Questionnaire

Section 1: Screening questions

1. Have you ever used the Alipay chatbot for more than 5 times in Nanjing?

a. Yes, please continue to answer b. No, please stop to answer

Section 2: Variable questions

Variable	Questions	1	2	3	4	5
E-service agent market (Alharbi, 2020)						
Interaction	2. The chatbot service agent has the knowledge to answer customers' questions.					
	3. The chatbot service agent is never too busy to answer customers' requests					
	4. The chatbot service agent gives customers individual attention.					
	5. The chatbot service agent is consistently courteous with customers					
Perceived enjoyment	6. It is enjoyable to share a conversation with the chatbot service agent					
	7. I was absorbed in the conversation with the chatbot service agent					
	8. The conversation with the chatbot service agent was exciting.					
	9. I enjoy choosing products more if the chatbot service agent recommends them					

Customization	10. The brand offers products and services I could not find in another company.					
	11. If I change companies, the products and services would be as customized as I have now.					
	12. I feel that using this chatbot and transacting with this service agent meets my personal needs					
	13. This service agent provides information about products according to my preferences					
Problem-solving	14. The chatbot service agent willingly handles returns and exchanges.					
	15. When a customer has a problem, the service agent is sincerely interested in solving it.					
	16. The conversational agent can handle customer complaints directly.					
	17. I am confident that the service agent can do the job.					
Perceived ease of use	18. Using chatbot service does not require much mental effort.					
	19. I find it easy to get and use the chatbot service to do what I want it to do.					
	20. My interaction with the chatbot service is clear and understandable					
	21. I find that the chatbot service is easy to use.					
TAM model (Chung et al., 2020)						

Perceived usefulness	22. Using the chatbot service improves my performance in my job					
	23. Using the chatbot service in my job increases my productivity					
	24. Using the chatbot service enhances my effectiveness in my job					
	25. I find the chatbot service to be helpful in my job					
Affective attitude (Chung et al., 2020)						
Attitude	26. I think it would be perfect to use the chatbot service rather than other materials					
	27. Using the chatbot service rather than other materials would be desirable.					
	28. It would be much better for me to use the chatbot service.					
	29. I find that the chatbot service is easy to use.					
Customer brand relationship (Cheng & Jiang, 2021a)						
Satisfaction	30. I believe I am happy with this brand					
	31. I believe both this brand and I benefit from the relationship					
	32. Generally speaking, I am pleased with the relationship this brand has established with me					
	33. I believe I enjoy dealing with this brand					
Brand Trust	34. I believe the brand treats me fairly and justly					

	35. I believe whenever the brand makes an important decision, I know it will be concerned about me					
	36. I believe the brand can be relied on to keep its promises					
	37. I believe the brand takes my opinions into account when making decisions					
Commitment	38. I believe I feel very confident about the brand's skills					
	39. I believe I feel that the brand is trying to maintain a long-term commitment to me					
	40. I believe I can see that the brand wants to maintain a relationship with me					
	41. I believe that compared to other brands, I value my relationship with this brand					

Thank you for your answering!

Section 3: Demographic information

42. Your gender: (a) Male (b) Female (c) other

43. Your age group pleases:

(a) 20 or less (b) 21 – 30 (c) 31 - 40

(d) 41 – 50 (e) 51 or more

44. Your gross annual household income (CNY):

(a) 20,000 or less (b) 20,001 - 50,000 (c) 50,001 - 100,000

(d) 100,001 - 150,000 (e) 150,001 or more

45. What is your educational status?

(a) Secondary school or less (b) Undergraduate (c) Graduate

(d) Post Graduate (e) Other

46. Your employment category:

(a) Management (b) Student

(c) Government (d) Employee

(e) Self-Employee (f) Other

Thank you for your answer!