WHAT ROLE DOES AI CHATBOT PERFORM IN THE F&B INDUSTRY?  
PERSPECTIVE FROM LOYALTY AND VALUE CO-CREATION:  
INTEGRATED PLS-SEM AND ANN TECHNIQUES

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ABSTRACT

Purpose: This study examines the process formation of customer loyalty and customer value co-creation towards AI chatbots by exploring the successive effects of perceived value aspects, perceived information quality, technological self-efficacy for online trust, aspects of loyalty, and value co-creation.

Theoretical framework: The increasingly strong reception of humans for a new wave of digitalization has promoted the need to learn about customer loyalty and customers’ value co-creation formation for businesses applying AI chatbots to their operations business to attract and retain customers. The study utilized the perceived value dimension, as well as perceived information quality, technological self-efficacy, and online trust, to comprehend loyalty and value co-creation.

Design/methodology/approach: The study was conducted using a self-administered questionnaire survey with 447 participants, who had used Pizza Hut’s AI chatbot service in Vietnam. The data was analyzed by integrating two techniques: partial least square structural equation modeling (PLS-SEM) and artificial neural networks (ANN).

Findings: The results show that aspects of perceived value, perceived information quality, and technological self-efficacy all have a significant impact on online trust except hedonic value, which in turn leads to the formation of aspects of loyalty and high ability to create value co-creation. The analysis results show that perceived information quality has a stronger impact on online trust than technological self-efficacy. In addition, the non-linear results from the ANN analysis show that attitudinal loyalty has relatively stronger importance for value co-creation than behavioral loyalty.

Research, Practical & Social Implication: This study contributes to the emerging literature on the use of AI chatbots by investigating the possibility of consumers and providers co-creating value. Second, in this study, the authors delved into the internal aspects of loyalty and separated it into two primary aspects, behavioral and attitudinal, in order to clarify their impact on the factors that influence AI chatbot and value co-creation. In conclusion, this research contributes to the existing body of knowledge by providing a more multidimensional perspective on theories.
Originality/value: The integration of PLS-SEM and ANN techniques into the analysis to simultaneously explore both linear and non-linear mechanisms of this study explained the influence of aspects of perceived value, perceived information quality, and technological self-efficacy on aspects of loyalty and value co-creation via online trust in AI chatbots context. In addition, this study extends the perceived value to explore the impact of internal and external personal factors on AI chatbots.

Keywords: AI chatbot, perceived value, loyalty, value co-creation, Vietnam, PLS-SEM, ANN.

QUE PAPEL O AI CHATBOT DESEMPENHA NO SETOR DE F&B?
PERSPECTIVA DA COCRIAÇÃO DE FIDELIDADE E VALOR: TÉCNICAS PLS-SEM E ANN INTEGRADAS

RESUMO

Objetivo: Este estudo examina o processo de formação de lealdade do cliente e de co-criação de valor do cliente em relação aos chatbots de IA, explorando os efeitos sucessivos dos aspectos do valor percebido, qualidade da informação percebida, autoeficácia tecnológica para a confiança online, aspectos de lealdade e co-criação de valor.

Quadro teórico: A recepção cada vez mais forte de seres humanos para uma nova onda de digitalização promoveu a necessidade de aprender sobre a lealdade do cliente e a formação de co-criação de valor dos clientes para as empresas que aplicam chatbots de IA às suas operações para atrair e reter clientes. O estudo utilizou a dimensão de valor percebido, bem como a qualidade da informação percebida, a autoeficácia tecnológica e a confiança on-line, para compreender a lealdade e a cocriarção de valor.

Design/metodologia/abordagem: O estudo foi realizado utilizando um questionário autoadministrado com 447 participantes, que utilizaram o serviço de bate-papo de IA da Pizza Hut no Vietnã. Os dados foram analisados integrando duas técnicas: modelagem parcial de equações estruturais pelo menos quadradas (PLS-SEM) e redes neurais artificiais (ANN).

Descobertas: Os resultados mostram que aspectos do valor percebido, da qualidade da informação percebida e da autoeficácia tecnológica têm um impacto significativo na confiança online, exceto o valor hedônico, que por sua vez leva à formação de aspectos de lealdade e alta capacidade de criar co-criação de valor. Os resultados da análise mostram que a percepção da qualidade da informação tem um impacto mais forte na confiança online do que a autoeficácia tecnológica. Além disso, os resultados não-lineares da análise da ANN mostram que a lealdade comportamental tem uma importância relativamente maior para a cocriarção de valor do que a lealdade comportamental.

Pesquisa, Implicação Prática & Social: Este estudo contribui para a literatura emergente sobre o uso de chatbots de IA, investigando a possibilidade de consumidores e provedores co-criarem valor. Em segundo lugar, neste estudo, os autores se aprofundaram nos aspectos internos da lealdade e a separaram em dois aspectos primários, comportamental e comportamental, a fim de esclarecer seu impacto nos fatores que influenciam a cocriarção do chatbot e do valor da IA. Em conclusão, esta pesquisa contribui para o corpo de conhecimento existente, fornecendo uma perspectiva mais multidimensional sobre as teorias.

Originalidade/valor: A integração das técnicas PLS-SEM e ANN na análise para explorar simultaneamente mecanismos lineares e não lineares deste estudo explicou a influência dos aspectos do valor percebido, da qualidade da informação percebida e da autoeficácia
tecnológica em aspectos de lealdade e co-criação de valor através da confiança online no contexto dos chatbots de IA. Além disso, este estudo estende o valor percebido para explorar o impacto de fatores pessoais internos e externos nos chatbots de IA.

Palavras-chave: IA chatbot, valor percebido, lealdade, valor co-criação, Vietnã, PLS-SEM, ANN.

1 INTRODUCTION

With impressive statistics reaching 85% of the intention to use or continue to use AI-based applications in business operations of businesses in 2020, it has shown the rapid development speed and the tendency of humans to accept new technology applications more openly and effectively (Magoulas & Swoyer, 2020). In which, conversational AI (including voice assistants and AI chatbots) is one of the applications with the potential to become the mainstream technology in practically every vertical industry in the future with the global market size expected to grow from USD 10.7 billion in 2023 to USD 29.8 billion in 2028 at a compound annual growth rate of 22.6% (Jessica Lis, 2022; MarketsandMarkets, 2023). Especially AI chatbot, a computer program based on AI technology to simulate human conversation using natural language processing (NLP) and machine learning (Behera et al., 2021; Calvaresi et al., 2021). This is an application that plays an important role in helping businesses connect with customers more effectively and improve their satisfaction with the business thanks to its flexibility, immediacy, high accuracy, wide reach, and low cost (Nuruzzaman & Hussain, 2020).

Although the study about chatbots is not uncommon, the study on chatbots based on AI technology according to the knowledge of the authors is still not popular among researchers today, especially in the F&B industry. Besides, in fact, there is still almost no study explaining customers’ intention to participate in the value co-creation process after experiencing AI chatbot service from the provider. Moreover, previous studies when investigating the effects of loyalty related, only researched the general theory of loyalty (Paringan & Novani, 2022) or only researched a certain aspect such as behavioral loyalty (Liu et al., 2020), or attitudinal loyalty (Casper Ferm & Thaichon, 2021). Almost no previous studies have examined the impact of loyalty on value co-creation, especially considering both behavioral and attitudinal loyalty aspects in the context of AI chatbots. In addition, previous studies related to chatbots mostly used the PLS-SEM method to analyze and check the linear relationship between structures in their model (Ashfaq et al., 2020; Kwangsawad & Jattamart, 2022; Wang et al., 2022). Until now, there are still very
few studies using the ANN analysis method to evaluate the nonlinear relationship between structures.

To clarify the issues and contribute to filling the research gaps mentioned above, this study has three main objectives as follows: (1) Discovering the impact of dimensions of perceived value, perceived information quality, and technological self-efficacy on customer loyalty in both attitudinal and behavioral aspects through customer online trust towards AI chatbots. (2) Clarifying the impact of attitudinal and behavioral loyalty on value co-creation. (3) Determining the influence of dimensions of perceived value, perceived information quality, and technological self-efficacy on the degree of customer involvement in creating value co-creation via customer loyalty in both attitudinal and behavioral aspects towards the AI chatbot.

2 THEORETICAL FRAMEWORKS
2.1 LITERATURE REVIEW
2.1.1 Review AI Chatbot

Currently, AI chatbots are being recognized by researchers as a significant technological trend in customer service support (Chung et al., 2020; R. Roy & Naidoo, 2021). According to the study by Ruan & Mezei (2022), it was found that AI chatbots will better meet user expectations than human frontline employees in an online shopping environment when the product attribute is functional and vice versa when the product attribute is experiential. Meanwhile, research by Li & Zhang (2023) has shown that both push effects (low adaptability and low empathy) and pull effects (connectivity, visibility, association, and personalization) have a positive effect on switching customer behavior from human-mediated services to AI chatbot-mediated services. Besides, research by Kwangsawad & Jattamart (2022) on the sustainable adoption of AI chatbots has proved that customers' attitudes and intentions to use AI chatbots can be directly affected by perceived privacy and time risk. More recently, Hsu & Lin (2023) conducted e-service quality of AI chatbot assessments by examining the impact of core service, service rangey quality, and conversational quality of AI chatbot on customer satisfaction and customer loyalty.

In general, previous studies are only focused on factors affecting attitude, intention to use/continue to use, customer satisfaction, and customer loyalty to AI chatbots. However, the research on the ability to participate in the customer's value co-
creation process for AI chatbots is still quite new, especially in the field of F&B. Therefore, to go a step further in the research literature related to AI chatbots, this study will investigate how the factors influencing AI chatbot have an impact on aspects of loyalty and value co-creation.

2.1.2 Value Co-Creation

Introduced and defined for the first time in the study of Prahalad & Ramaswamy (2004), value co-creation refers to the collaborative interaction to create value between beneficiaries and suppliers. It requires two-way communication between customers and suppliers to help suppliers better understand and respond to customer needs and preferences (Buonincontri et al., 2017). Accordingly, the customer is empowered to act as a key participant in sharing information, knowledge, and new ideas that enhance the value of the product or service they are using (Preikschas et al., 2017). Meanwhile, companies act as facilitators in improving products or services from customer contributions and turning their ideas into reality, helping customers feel motivated and ready to participate in the company's value co-creation (Opata et al., 2021; Payne et al., 2008). Naturally, the result of this effort is that the company can enhance customer satisfaction, reliability, and loyalty (Cossio-Silva et al., 2016).

On the other side, previous studies on value co-creation have shown the flexibility of the theory when it can be conceptualized and applied in many different fields and contexts (Balaji & Roy, 2017; Wahab et al., 2022). Besides, although value co-creation has been included in research in the context of AI, the number and context of research are still limited. Especially, there are still almost no previous studies examining value co-creation in the context of AI chatbots. Therefore, recognizing the importance of value co-creation theory when applied to business practice and the gaps in previous studies (Lalicic & Weismayer, 2021; Nadeem et al., 2020), this study decided to use value co-creation as a main and core theory for investigating customer behavior towards AI chatbots in the F&B field.

2.1.3 Perceived Value

Consumers' overall evaluation of the utility of a product based on their perception of what is received and what is given is called perceived value (Zeithaml, 1988). Perceived value includes many different aspects, has a multidimensional structure, and
the dimensions will vary depending on the domain, according to the study of Sweeney & Soutar (2001) and Al-Sabbahy et al (2004). Indeed, the study by Sweeney & Soutar (2001) demonstrated that consumers do not merely judge a product based on its functionality and expected performance (utilitarian value) but also based on the emotional level as pleasure, enjoyment (hedonic value) derived from the product and the social results of what the product does for others (social value). Therefore, to give a more complete evaluation of a customer’s perceived value in the AI chatbot context, the present study divides consumers’ perceived value into 3 dimensions: utilitarian value, hedonic value, and social value like previous studies of Evelina et al (2020).

Utilitarian value is defined as the customer's evaluation of the functional attributes of a product (e.g., timesaving, cost, utility, performance, quality, etc.) (Blythe, 2005). Consideration of these functional attributes is assessed by customers based on their past experiences, acquired knowledge, and available information through their purchasing and consumption activities (Randheer, 2015). Recently, in the field of AI, utilitarian value refers to the ability of AI products to effectively fulfill customers' goals in their lives (Frank et al., 2021).

Hedonic value is a value based on a customer's intrinsic buying motivation driven by a desire to achieve some sort of emotion (e.g., pleasure, stimulation, entertainment, and experience happiness while shopping…) for self-satisfaction (Lamidi & Rahadhini, 2018). In essence, hedonic values are not part of the main function of the product (Dhar & Wertenbroch, 2000), it is the intangible value that customers are always looking for to feel and experience in shopping (H. Kim, 2006). The authors expanded the concept of hedonic value in the context of AI chatbots as values in terms of customers’ emotional experiences when using AI chatbots based on a study by Bardhi & Eckhardt (2012).

Social value is defined as the benefit of a product or service in helping an individual gain social recognition and pride (Evelina et al., 2020). It refers to the degree of value that consumers gain in maintaining and expanding their relationships through interactions with others (To et al., 2007). In previous studies, social value has been examined in many different contexts such as social commerce (Gan & Wang., 2017), smart speakers (Ashfaq et al., 2021), and online shopping (X. Zhang et al., 2019). The authors have extended the concept of social value in the context of AI chatbot as values of recognition, the ability to achieve a good impression of others on an individual through using AI chatbot.
2.1.4 Perceived Information Quality

Perceived information quality refers to the customer's evaluation of the relevance, uniqueness of the information, and its up-to-date quality (A. J. Kim & Johnson, 2016). Accordingly, DeLone & McLean (1992) emphasize that timely and accurate information is crucial to the success of an information system. Providing high-quality information will save customers time and effort to process useless information, thereby improving customer satisfaction with brands (DeLone & McLean, 2002; Zheng et al., 2013). Based on studies by Wien & Peluso (2021); Wirtz et al (2018), in the AI chatbot context, perceived information quality refers to customers' perception of the AI chatbot's ability to provide complete and complete information about products based on mechanical or analytical system learning. Therefore, to investigate the impact of perceived information quality on customer behavior, the authors will scrutinize the impact of information quality perceived by AI chatbot customers on their online trust in the context of AI chatbot.

2.1.5 Technological Self-Efficacy

The concept of self-efficacy was born very early and is defined as the ability to generate self-motivation and self-regulate in terms of cognition and behavior of an individual to meet a particular situational requirement (Wood & Bandura, 1989). It is the main factor in creating the intrinsic motivation of the individual consumer (Davis et al., 1989). Based on the notion of self-efficacy, Keengwe (2007) defined technological self-efficacy as an individual's perception of their ability to use technology-related tools (Keengwe, 2007). It refers to an individual's level of confidence and comfort in using technology-based products. Previously, researchers have measured technological self-efficacy in various aspects such as internet self-efficacy, online technological self-efficacy, and mobile technological self-efficacy (Jokisch et al., 2020; Menon et al., 2017). Likewise, for this study, the authors refer to technological self-efficacy as confidence in customers' ability to use AI chatbots. Accordingly, customers who are confident in their own technological capabilities will have a more positive attitude toward receiving and using AI chatbot services (Al-Maroof et al., 2021).
2.1.6 Online Trust

According to D. Kim & Benbasat (2009), trust is the attitude of believing and expecting that an individual's weaknesses will not be exploited in a risky situation. In the context of e-commerce, online trust is reliance on a brand's business activities in general electronically (Bock et al., 2012; Shankar et al., 2002). Based on previous research papers on online trust (Busalim et al., 2021; X. Yang, 2021), this research paper refers to customers developing their trust based on personal experiences during direct interaction with AI chatbots. According to Y. Kim & Peterson (2017), the consequences of online trust investigated in the present meta-analysis include satisfaction, attitude, purchase intention and repeat purchase, intention to use the website, and customer loyalty. Likewise, applying to the field of AI chatbot service, online trust can be created from a trusting attitude with expectation and customer satisfaction in the interactive process generating transactions with AI chatbot, thereby affecting customer loyalty toward AI chatbot, and increasing the ability to participate in the process of value co-creation of customers.

2.1.7 Customer Loyalty

Customer loyalty is defined as repeat purchase behavior with a certain retailer, as a preference for a certain brand, and in favor of word of mouth (Zeithaml et al., 1996). It is seen as an important competitive advantage in bringing about the long-term success and profitability of a business (Srivastava & Rai, 2013). Some previous studies on consumer behavior have identified factors affecting customer loyalty to retailers including perceived value (Molinillo et al., 2021), reputation, and website quality (Rodríguez et al., 2020; S. K. Roy et al., 2014). In this study, to gain a deeper understanding of loyalty in the context of AI chatbots, the authors divided customer loyalty into two main aspects: behavioral and attitudinal based on research by Berkowitz et al (1978) and Oliver (1999).

Behavioral loyalty refers to the frequency of repeat purchases by customers for the same brand over a certain period (Holbrook & Chaudhuri, 2001). It is considered the researchers' initial real measure of customer loyalty (Guadagni & Little, 1983). In the AI chatbot context, it can be understood as the behavior of customers in maintaining the use of a particular type of AI chatbot service. Based on the study of Sethuraman & Gielens (2014), behavior loyalty toward AI chatbots will become more important to suppliers as
their goal at that moment is to increase market share and profits. However, measuring behavior is not enough to understand the structure of loyalty (Oliver, 1999; Reichheld, 2003). Therefore, a new measure of loyalty was proposed, attitudinal loyalty (Mostafa & Hamieh, 2022).

Attitudinal loyalty is considered the psychological attachment of customers to products and suppliers (Amine, 2011). It demonstrates a customer's level of commitment, willingness to spend, and word-of-mouth referrals for a particular brand (Ong et al., 2016). Accordingly, brands that achieve customer attitudinal loyalty will easily raise prices higher for a particular product since this customers group will not hesitate to spend more money on brands to which they have attitudinal loyalty (Holbrook & Chaudhuri, 2001; J. Zhang & Bloemer, 2008). In the context of AI chatbots, based on the discovery of Casper Ferm & Thaichon (2021), to increase customer attitudinal loyalty, the supplier always tries to create a good emotional connection with its customers by designing AI chatbots that can personalize customer data, and make appropriate recommendations when interacting with customers. Thereby creating positive psychology for customers when using AI chatbots and making them have no intention of using other alternative AI chatbot products.

2.2 HYPOTHESES DEVELOPMENT

2.2.1 The Relationship Between Dimensions of Perceived Value (UV, HV, SV) and Online Trust

Based on the study of Dhar & Wertenbroch (2000) and Voss et al (2003), in the AI chatbot context, utilitarian value refers to the speed of message response, order support, ease of navigation, ease of use, and personalized customer data. Among them, ease of navigation and ease of interface use has been shown to influence customer trust and is an important part of website trust (Cyr, 2008). Besides, these utilitarian factor-related values have been investigated and confirmed by Hanzaee & Andervazh, (2012) that they have a direct and positive impact on brand trust through the credibility and reliability of the brand (Ok et al., 2011). In the AI chatbot context, responding to messages quickly, helping customers save time in ordering, intuitive images, as well as ease of navigation, and ease of interface to use will have a direct and positive impact on customers' perceptions when using the service, thereby affecting customers' online trust.
in AI chatbot service. Thus, based on the above arguments, the first hypothesis can be drawn as follows:

**H1.** Utilitarian value positively affects online trust.

Developed from the definition in the study of Hirschman & Holbrook (1982), in the AI chatbot context, hedonic value refers to the multisensory, imaginative, and emotional aspects of one’s experience with AI chatbots. Previously, S. H. Chen & Lee (2008) indicated that hedonic value has no direct impact on online trust, but it indirectly affects online trust through customer attitude (Albayrak et al., 2020). Accordingly, when performing shopping behaviors and receiving positive values, customers will have a more positive attitude toward the service system (Hamari & Koivisto, 2015), thereby increasing the online trust level of customers in that service system. In addition, De Wulf et al (2006) also asserted that the level of commitment and trust of customers will be higher if they have more fun using the website. For the AI chatbot context, when customers feel emotional factors such as excitement, novelty, happiness, and joy that the AI chatbot brings to them when using, customers will have a positive attitude toward the AI chatbot leading to an increase in the level of customer online trust in the AI chatbot service. Therefore, the present study hypothesizes that:

**H2.** Hedonic values positively affect online trust.

Based on the study of S. B. Kim et al (2013), social value in the context of AI chatbots can be interpreted as the value of social acceptance and the capacity to leave a positive impression on others via the use of AI chatbots. According to Hamari & Koivisto (2015), social recognition and appreciation will affect customers’ attitudes and intentions to continue using the products. Indeed, customers are more likely to feel satisfied with products for which they receive acceptance, positive feedback from friends, and social support via using technology (Gan & Wang, 2017; Y. H. Kim et al, 2013). On the other hand, online trust has a positive impact on customer attitudes toward online purchases Gurung & Raja (2016). In addition, similar to previous studies of Gurung & Raja (2016) and Jadil et al (2022), in the AI chatbot context, customers will feel satisfied and have a positive attitude toward utilizing the AI chatbot when it satisfies their expectations in terms of social interactions and personal relationships, thereby affecting customers' online trust in the AI chatbot. Consequently, the following hypothesis is developed:

**H3.** Social values positively affect online trust.
2.2.2 The Relationship Between Perceived Information Quality and Online Trust

Perceived information quality in the context of AI chatbots refers to the AI chatbot's capacity to satisfy customers' information requirements, such as accuracy, timeliness, and relevancy of information about products on the AI chatbot platform (Alharbi, 2021; Alshikhi & Abdullah, 2018). Research by Goodhue & Thompson (1995) has shown that customers evaluate information sources they receive as authoritative when they reflect accurate information in detail and have a high level of reliability. This led to the customer's perception of information quality positively affecting customer trust (Nicolaou & McKnight, 2006). Similarly, in the AI chatbot context, customers are more likely to trust the AI chatbot platform when they are aware of the quality of information regarding the completeness and accuracy that the AI chatbot brings in the process of use. Therefore, based on previous literature, the present study posited the following hypothesis:

H4. Perceived information quality positively affects online trust.

2.2.3 The Relationship Between Technological Self-Efficacy and Online Trust

Based on the study of Venkatesh & Davis (1996), in the AI chatbot context, technological self-efficacy is understood as a self-assessment of an individual's competence in using the AI chatbot. Accordingly, those who are confident in their capacity to use new technology without difficulty will have a positive attitude toward its use (Lee, 2021). Besides, Al-Maroor et al (2021) verified that digital technological self-efficacy has a positive impact on the intention to continue using technology in e-learning environments. On the other hand, Abdul-Halim et al (2022) and Gurung & Raja (2016) indicate that trust has a positive effect on the intention to continue using e-wallets, simultaneously, the degree of customer trust is also proportionate to their attitude regarding online purchases. Based on the above literature, in the AI chatbot context, the authors deduce that customers with high technological self-efficacy will have a positive attitude toward using AI chatbot, leading to increased intention to continue using AI chatbot. This contributes to helping providers improve customers' online trust in the company's AI chatbot platform. Hence, the present study hypothesizes as follows:

H5. Technological Self-Efficacy positively affects online trust.
2.2.4 The Relationship Between Online Trust and Aspects of Loyalty (ALO, BOL)

Developed from the definition in the study of Eastlick & Lotz (2011), online trust in the AI chatbot context refers to the level of faith customers have in AI chatbot platforms based on the credibility, benevolence, and competence of AI chatbot suppliers in carrying out their promises in the future. Forgas et al (2010) and Şahin et al (2011) demonstrated that when customers trust a brand, they are more likely to remain loyal to it. Besides, trust is an important factor in promoting customer loyalty (Ong et al., 2016) and a determinant of loyalty in terms of both customer behavior and attitude toward the brand (Holbrook & Chaudhuri, 2001). According to various research from the past, behavioral loyalty and attitudinal loyalty have been verified that they have a positive effect on online trust in the financial services industry (Rajaobelina et al., 2014). Similarly, in the AI chatbot context, customers will tend to remain loyal to the AI chatbot platform when they believe that it can meet their expectations. This is demonstrated through increasing usage frequency, sharing information, introducing the AI chatbot to others (behavioral loyalty), maintaining a positive attitude, and supporting the AI chatbot (attitudinal loyalty). Thus, the present study posited the following hypotheses:

H6a. Online trust positively affects behavioral loyalty.
H6b. Online trust positively affects attitudinal loyalty.

2.2.5 The Relationship Between Aspects of Loyalty (ALO, BOL) and Value Co-Creation

In the AI chatbot context, behavioral loyalty refers to customers continually using AI chatbots when they have demand instead of using other alternative platforms (Cossío-Silva et al., 2016). Attitudinal loyalty refers to the customer's positive attitude and support toward the AI chatbot in front of the opinions of the public (Saini & Singh, 2020). Previously, studies by C. F. Chen & Wang (2016) and C. M. Chen et al (2013) confirmed that customer satisfaction has a positive impact on loyalty and two aspects of loyalty (behavioral and attitudinal). On the other side, Etgar (2008) and Muniz & O’Guinn (2001) asserted that value co-creation can help suppliers improve customer satisfaction by allowing customers to be directly involved in the production process and service provider. The evidence is that value co-creation has been demonstrated that have a direct and positive effect on customer satisfaction (Arica & Çorbaci, 2020; Opata et al., 2020). Based on the above literature, the authors argue that when value co-creation takes place,
customers will feel satisfied with the AI chatbot service they use, thereby loyalty in both behavioral and attitudes aspects will be formed. This argument shows that aspects of loyalty (behavioral, attitudinal) and value co-creation have an impact on each other via satisfaction. Therefore, the present study proposes the following hypotheses:

H7. Behavioral loyalty positively affects value co-creation.

H8. Attitudinal loyalty positively affects value co-creation.

3 METHODOLOGY
3.1 DATA COLLECTION METHOD AND SAMPLE CHARACTERISTICS

Firstly, considering to the in terms of the novelty and the lack of research information on AI chatbots in Vietnam, the authors decide to use an exploratory design to assess the market acceptance of Pizza Hut's AI chatbot service by assessing customer behavior. Nextly, to guarantee the achievement of the research objectives as well as the validity and reliability of the research findings, a quantitative approach is used in this study. Then, to test hypotheses developed based on existing theories to find answers to the research problem, the authors choose the positivism paradigm as the main research
paradigm. Besides, the questionnaire technique is also used in this study as a common way to gather primary data (Kumar, 2005).

In addition, to be able to select appropriate samples deliberately to ensure that all samples have similar characteristics, the judgmental sampling method to perform this study, similar to research by L. T. Nguyen et al (2022). The respondents have experience using Pizza Hut's AI chatbot service to order pizza. Finally, the study used G*Power statistical software, and Sloper to determine the minimum sample size to be collected for this study (J. Hair et al., 2017; Tan & Ooi, 2018). The calculation results show that the minimum sample size to make this study as reliable as possible is 114 samples. Therefore, after surveying and discarding unqualified samples, this study has 447 samples eligible for further analysis, this number exceeds the required number of sample sizes required.

3.2 RESPONDENT PROFILE

As shown in Table 1, females made up 76.73% of the total sample, and 23.27% are male with the age group being mainly adults from 20 to 35 years old, accounting for 70.02%, while respondents with age from 36 to 50 years old account for 0.89% and below 20 years old accounts for 29.08%. Next, respondents with the frequency of using Pizza Hut's AI chatbot from 1 to 5 times per month accounted for the majority with a percentage up to 94.85%, the remaining 4.03% with frequency from 6 to 10 times and 1.12% with a frequency of above 10 times. Besides, Table 1 also shows that the monthly cost that respondents accept to spend to order Pizza Hut on the AI chatbot with the highest percentage fee is under VND 500,000, accounting for 82.33%, followed by fees from VND 500,000 to VND 1,000,000 accounted for 14.54%, from VND 1,000,01 to VND 5,000,000 accounted for 2.01% and finally the fee over VND 5,000,000 accounted for 1.12%. Additionally, channels help customers to access Pizza Hut's AI chatbot from the answers of 447 respondents with 590 choices about the type of channels shown in Table 1 showing that most respondents know about Pizza Hut's AI chatbot through friends and social networking platforms are the main with 41.7% and 38% respectively, the remaining 20.3% are known through the salesperson at Pizza Hut.

Table 1. Demographic profile of respondents

<table>
<thead>
<tr>
<th>Demographic characteristic</th>
<th>Frequency</th>
<th>Percentage</th>
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<tbody>
<tr>
<td>Gender</td>
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</tr>
<tr>
<td>Female</td>
<td>343</td>
<td>76.73%</td>
</tr>
<tr>
<td>Male</td>
<td>104</td>
<td>23.27%</td>
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<td>Below 20 years old</td>
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<td>29.08%</td>
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<td>20 – 35 years old</td>
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<td>70.02%</td>
</tr>
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</table>
3.3 MEASUREMENTS

To reduce neutral responses, create a higher degree of dispersion, and increase accuracy in discriminating between respondents’ opinions (Bass et al., 1974), the authors used a 7-point Likert scale instead of using a 5-point Likert scale to measure customer behavior and attitude when using Pizza Hut’s AI chatbot. In addition, to make the items of constructs more reliable, the authors have approved the previous studies to adjust them to suit the object and research topic that this study is aimed at, specifically Pizza Hut's AI chatbot. Specifically, the utilitarian value was adjusted to Evelina et al (2020). Hedonic value was adapted from Avcilar & Ozsoy (2015); Paramitha et al (2022); Tariyal et al (2022). Social value was adapted from Evelina et al (2020); Yu & Huang (2022). Perceived information quality was adjusted to Ruan & Mezei (2022). Technological self-efficacy was adapted from Shiau et al (2020). Online trust was adapted from Ameen et al (2021); Zhu et al (2022). Finally, behavioral loyalty and attitudinal loyalty were adapted from Oliver & Swan (1989) and Kaur & Soch (2012), respectively.

4 RESULTS AND DISCUSSION
4.1 RESULTS
4.1.1 Common Method Bias

Due to the data for exogenous and endogenous variables being collected from a single source, common method bias is likely to emerge. Thus, to assess the potential threat of CMB and solve this issue, the authors used procedural and statistical procedures in the research data analysis (Leong et al., 2018) and applied the cross-sectional design to the research (Tan & Ooi, 2018). Procedurally, all respondents will be notified before taking the survey that their personal information and response will be anonymized and confidential by the researcher and there is no correct or incorrect response to any question.
in the entire survey. Statistically, the results obtained from conducting Harman's single factor analysis show that the KMO and Bartlett’s Test of 0.95 is above the minimum of 0.5 and there is a single component that accounts for 18.79% of the overall variation within the permitted threshold of less than 50% (Ooi, Hew, Leong, et al., 2018). Hence, this CMB issue is not likely to occur for the dataset.

4.1.2 Assessing the Measurement Model

Prior to the hypotheses in the structural model being tested, the measurement model needs to be evaluated and validated first. To evaluate the measurement model, the authors need to test the reliability and validity of the measurement model (J. Hair et al., 2017). Firstly, the reliability in this study is tested using Cronbach's Alpha (CA), composite reliability (CR), and Dijkstra-Henseler's rho (pA) (Teo et al., 2015). Accordingly, as shown in Table 2, the minimum values of CA, CR, and pA are 0.881, 0.912, and 0.894, respectively. This result shows that CA, CR, and pA are verified, and all constructs have significant reliability since all three values are greater than the threshold value of 0.7 (Foo et al., 2018; Tan & Ooi, 2018).

Nextly, the convergent validity in this study was tested using the average variance extracted (AVE) and factor loadings (FL) (Hair Jr et al., 2016). As shown in Table 2, the lowest AVE value of 0.675 is greater than the minimum threshold of 0.5, concurrently, all FL values between 0.763 and 0.938 are larger than the threshold value of 0.7 (J. Hair et al., 2017; J. F. Hair et al., 2021). Consequently, the convergent validity of this study has been confirmed. Finally, the discriminant validity in this study was evaluated based on two criteria Fornell-Larcker’s criterion (Fornell & Larcker, 1981), and cross-loadings (Henseler et al., 2015). Accordingly, the results displayed in Table 3 indicate that all the square roots of AVE have a value greater than their correlation coefficients (Henseler et al., 2015). Simultaneously, the results of the cross-loadings from Table 4 also show that all loadings have a high load to the respective constructs, whereas having a low load to the irrelevant constructs. Therefore, the discriminant validity is verified in this study.

Table 2 Convergent Validity and Construct Reliability

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Items</th>
<th>Factor Loadings (FL)</th>
<th>Cronbach's Alpha (CA)</th>
<th>Dijkstra Henseler rho_A (pA)</th>
<th>Composite Reliability (CR)</th>
<th>Average Variance Extracted (AVE)</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>UV</td>
<td>UV1</td>
<td>0.822</td>
<td>0.881</td>
<td>0.894</td>
<td>0.912</td>
<td>0.675</td>
<td>2.495</td>
</tr>
<tr>
<td></td>
<td>UV2</td>
<td>0.875</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.179</td>
</tr>
<tr>
<td></td>
<td>UV3</td>
<td>0.810</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2.148</td>
</tr>
</tbody>
</table>
Table 3 Fornell-lacker criterion

<table>
<thead>
<tr>
<th>Latent Construct</th>
<th>ALO</th>
<th>BOL</th>
<th>CVC</th>
<th>HV</th>
<th>OT</th>
<th>PIQ</th>
<th>SV</th>
<th>TSE</th>
<th>UV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO</td>
<td>0.930</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BOL</td>
<td>0.824</td>
<td>0.910</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CVC</td>
<td>0.832</td>
<td>0.804</td>
<td>0.885</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HV</td>
<td>0.176</td>
<td>0.202</td>
<td>0.201</td>
<td>0.880</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OT</td>
<td>0.807</td>
<td>0.811</td>
<td>0.769</td>
<td>0.193</td>
<td>0.892</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PIQ</td>
<td>0.791</td>
<td>0.850</td>
<td>0.776</td>
<td>0.198</td>
<td>0.879</td>
<td>0.900</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SV</td>
<td>0.766</td>
<td>0.751</td>
<td>0.721</td>
<td>0.172</td>
<td>0.824</td>
<td>0.793</td>
<td>0.881</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TSE</td>
<td>0.741</td>
<td>0.795</td>
<td>0.791</td>
<td>0.177</td>
<td>0.745</td>
<td>0.762</td>
<td>0.715</td>
<td>0.906</td>
<td></td>
</tr>
<tr>
<td>UV</td>
<td>0.372</td>
<td>0.408</td>
<td>0.359</td>
<td>0.052</td>
<td>0.492</td>
<td>0.452</td>
<td>0.378</td>
<td>0.323</td>
<td>0.822</td>
</tr>
</tbody>
</table>

Source: by the authors

Table 4 Cross-Loadings

<table>
<thead>
<tr>
<th>Latent Construct</th>
<th>ALO</th>
<th>BOL</th>
<th>CVC</th>
<th>HV</th>
<th>OT</th>
<th>PIQ</th>
<th>SV</th>
<th>TSE</th>
<th>UV</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO1</td>
<td>0.923</td>
<td>0.783</td>
<td>0.773</td>
<td>0.186</td>
<td>0.766</td>
<td>0.755</td>
<td>0.722</td>
<td>0.704</td>
<td>0.350</td>
</tr>
<tr>
<td>ALO2</td>
<td>0.938</td>
<td>0.752</td>
<td>0.772</td>
<td>0.169</td>
<td>0.739</td>
<td>0.720</td>
<td>0.717</td>
<td>0.690</td>
<td>0.353</td>
</tr>
<tr>
<td>ALO3</td>
<td>0.928</td>
<td>0.761</td>
<td>0.774</td>
<td>0.136</td>
<td>0.744</td>
<td>0.731</td>
<td>0.698</td>
<td>0.674</td>
<td>0.335</td>
</tr>
<tr>
<td>BOL1</td>
<td>0.784</td>
<td>0.911</td>
<td>0.752</td>
<td>0.163</td>
<td>0.739</td>
<td>0.781</td>
<td>0.705</td>
<td>0.759</td>
<td>0.364</td>
</tr>
<tr>
<td>BOL2</td>
<td>0.722</td>
<td>0.925</td>
<td>0.720</td>
<td>0.194</td>
<td>0.715</td>
<td>0.786</td>
<td>0.642</td>
<td>0.762</td>
<td>0.361</td>
</tr>
</tbody>
</table>

Source: by the authors
4.1.3 Assessing the Structural Model

Firstly, the authors eliminated the threat of multicollinearity before testing the proposed hypotheses by conducting a collinearity test (J. F. Hair et al., 2019). The results obtained from Table 2 shows that the values of variance inflation factors (VIF) ranging from 1.478 to 4.599 are lower than the threshold value of 5.0 (Tan & Ooi, 2018). Thus, the possibility of multicollinearity can be ruled out for this study.

Secondly, with 5,000 subsamples, no sign change, and 99 percent bias-corrected confidence intervals, the bootstrapping procedure was used in this study to collect the inferential statistics. According to the outcome of the hypotheses testing displayed in Table 5, UV, SV, PIQ, and TSE have a significant impact on OT with a p-value < 0.05, thus, the relationship of each hypothesis H1, H3, H4, and H5 is supported. However, hypothesis H2 about the relationship between HV and OT is unsupported because the p-value up to 0.436 is greater than the threshold value of 0.05. In addition, the results also
show that OT significantly affects ALO and BOL, simultaneously, ALO and BOL also significantly influence CVC due to all of them having a p-value < 0.001. As a result, the relationship of each hypothesis H6a, H6b, H7, and H8 are supported. Hence, based on the result of Table 5, the authors concluded that except for the relationship between HV and OT, the remaining variables are significantly correlated with each other.

4.1.4 The Predictive Relevance and Effect Size

The study evaluates the structural model’s predictive accuracy using the blindfolded approach to determine the Q² value. According to the study of J. Hair et al (2017), the predictive relevance of the model is confirmed when the Q² values are greater than zero and vice versa. Thus, based on the findings from column Q² (=1-SSE/SSO) of Table 6, the model’s predictive relevance in this study was confirmed. In addition, to achieve a minimum level of explanatory power for the model, the R² values must reach a certain value greater than the threshold value of 0.1 (Loh et al., 2021). In this study, the minimum value of R² was 0.651 (greater than 0.1), which explains substantial variance in the targeted endogenous construct (Loh et al., 2021).

Table 5 Hypotheses testing

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>PLS Path</th>
<th>Original Sample (O)</th>
<th>Sample Mean (M)</th>
<th>Standard Deviation (STDEV)</th>
<th>T Statistics ([O/STDEV])</th>
<th>P Values (p)</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1</td>
<td>UV → OT***</td>
<td>0.116</td>
<td>0.115</td>
<td>0.029</td>
<td>4.014</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H2</td>
<td>HV → OTNS</td>
<td>0.017</td>
<td>0.018</td>
<td>0.022</td>
<td>0.779</td>
<td>0.436</td>
<td>Unsupported</td>
</tr>
<tr>
<td>H3</td>
<td>SV → OT***</td>
<td>0.303</td>
<td>0.304</td>
<td>0.047</td>
<td>6.475</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H4</td>
<td>PIQ → OT***</td>
<td>0.503</td>
<td>0.503</td>
<td>0.054</td>
<td>9.248</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H5</td>
<td>TSE → OT*</td>
<td>0.105</td>
<td>0.104</td>
<td>0.041</td>
<td>2.556</td>
<td>0.011</td>
<td>Supported</td>
</tr>
<tr>
<td>H6a</td>
<td>OT → BOL***</td>
<td>0.811</td>
<td>0.812</td>
<td>0.020</td>
<td>40.554</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H6b</td>
<td>OT → ALO***</td>
<td>0.807</td>
<td>0.807</td>
<td>0.022</td>
<td>36.835</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H7</td>
<td>BOL → CVC***</td>
<td>0.371</td>
<td>0.372</td>
<td>0.069</td>
<td>5.383</td>
<td>0</td>
<td>Supported</td>
</tr>
<tr>
<td>H8</td>
<td>ALO → CVC***</td>
<td>0.526</td>
<td>0.525</td>
<td>0.063</td>
<td>8.352</td>
<td>0</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Note(s): a. UV = Utilitarian Value; HV = Hedonic Value; SV = Social Value; PIQ = Perceived Information Quality; TSE = Technological Self-Efficacy; OT = Online Trust; BOL = Behavioral Loyalty; ALO = Attitudinal Loyalty; CVC = Value Co-creation.

b. ***Significant at p < 0.001 level.
c. *Significant at p < 0.05 level
d. NS Not supported at p > 0.05 level

Source: by the authors

Table 6 Predictive Relevance (Q²) and R²

<table>
<thead>
<tr>
<th>Endogenous variable</th>
<th>Q² (=1-SSE/SSO)</th>
<th>Predictive Relevant</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO</td>
<td>0.558</td>
<td>Q²&gt;0</td>
<td>0.651</td>
</tr>
<tr>
<td>BOL</td>
<td>0.539</td>
<td>Q²&gt;0</td>
<td>0.658</td>
</tr>
<tr>
<td>CVC</td>
<td>0.569</td>
<td>Q²&gt;0</td>
<td>0.736</td>
</tr>
<tr>
<td>OT</td>
<td>0.654</td>
<td>Q²&gt;0</td>
<td>0.831</td>
</tr>
</tbody>
</table>

Source: by the authors
In a similar vein, the study assessed the effect size for each of the exogenous constructs using the Cohen $f^2$ values to observe the impact of each exogenous construct on the $R^2$ value of an endogenous construct (Cohen, 1988). Accordingly, the Cohen $f^2$ values will produce small, medium, and large effects with values of 0.02, 0.15, and 0.35, respectively (Kraft, 2020). As shown in Table 7, with the effect sizes ranging from 0.025 to 1.928, the exogenous construct has a small to large effect on the endogenous construct.

<table>
<thead>
<tr>
<th>Predictor Construct/Dependent Construct</th>
<th>ALO</th>
<th>BOL</th>
<th>CVC</th>
<th>OT</th>
</tr>
</thead>
<tbody>
<tr>
<td>ALO</td>
<td>0.338</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BOL</td>
<td>0.168</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OT</td>
<td>1.867</td>
<td>1.928</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PIQ</td>
<td></td>
<td></td>
<td></td>
<td>0.405</td>
</tr>
<tr>
<td>SV</td>
<td></td>
<td></td>
<td></td>
<td>0.185</td>
</tr>
<tr>
<td>TSE</td>
<td></td>
<td></td>
<td></td>
<td>0.025</td>
</tr>
<tr>
<td>UV</td>
<td></td>
<td></td>
<td></td>
<td>0.062</td>
</tr>
</tbody>
</table>

Source: by the authors

4.1.5 Artificial Neural Network (ANN) Analysis

The ANN analysis may assess the linear or nonlinear relationships between the structures and provide a more accurate level of prediction while the PLS-SEM analysis only focuses on the linear relationship between the structures (Leong et al., 2019; L. W. Wong et al., 2023). Therefore, to produce more convincing arguments and more precise predictions regarding customer behavior while utilizing AI chatbots, this study incorporated both PLS-SEM and ANN analysis methods, like the studies of (Ooi, Hew, & Lin, 2018). Accordingly, Figure 1 to 5 depicts the ANN model of 4 models A, B, C, and D respectively with the number of hidden neurons generated in ANN Model A and B being both 3 and in ANN Model C and D being 2 and 5, respectively.

Figure 2 ANN Model A

Figure 3 ANN Model B
Figure 4 ANN Model C

Figure 5 ANN Model D

Hidden layer activation function: Hyperbolic tangent
Output layer activation function: Identity
Source: by the authors
On the other side, to prevent the risk of model overfitting, a ten-fold cross-validation technique was applied in this study with 10 ANN networks and the ratio of data partitioned for training and testing is 90:10 (T. C. Wong et al., 2018). All the ANN Models A, B, C, and D's Root Mean Squared Error (RMSE) values, which are displayed in Table 8, are small, with mean values ranging from 0.492 to 0.602. This result indicates that all four ANN models have a good degree fit (S. Yang & Zeng, 2018). Besides, ANN Models A, B, C, and D can predict OT, BOL, ALO, and CVC with an accuracy of 99.39%, 99.32%, 99.30%, and 99.26% using RMSE values to calculate $R^2$.

<table>
<thead>
<tr>
<th>Model A</th>
<th>Model B</th>
<th>Model C</th>
<th>Model D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input: UV, SV, PIQ, TSE</td>
<td>Input: OT</td>
<td>Input: OT</td>
<td>Input: BOL, ALO</td>
</tr>
<tr>
<td>Output: OT</td>
<td>Output: BOL</td>
<td>Output: ALO</td>
<td>Output: CVC</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Neural network</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANN1</td>
<td>0.534</td>
<td>0.480</td>
<td>0.515</td>
<td>0.571</td>
<td>0.566</td>
<td>0.500</td>
<td>0.462</td>
<td>0.545</td>
<td></td>
</tr>
<tr>
<td>ANN2</td>
<td>0.595</td>
<td>0.600</td>
<td>0.543</td>
<td>0.571</td>
<td>0.578</td>
<td>0.553</td>
<td>0.560</td>
<td>0.725</td>
<td></td>
</tr>
<tr>
<td>ANN3</td>
<td>0.610</td>
<td>0.511</td>
<td>0.539</td>
<td>0.500</td>
<td>0.592</td>
<td>0.474</td>
<td>0.636</td>
<td>0.651</td>
<td></td>
</tr>
<tr>
<td>ANN4</td>
<td>0.501</td>
<td>0.569</td>
<td>0.561</td>
<td>0.436</td>
<td>0.606</td>
<td>0.574</td>
<td>0.505</td>
<td>0.436</td>
<td></td>
</tr>
<tr>
<td>ANN5</td>
<td>0.594</td>
<td>0.655</td>
<td>0.544</td>
<td>0.652</td>
<td>0.657</td>
<td>0.548</td>
<td>0.471</td>
<td>0.515</td>
<td></td>
</tr>
<tr>
<td>ANN6</td>
<td>0.590</td>
<td>0.548</td>
<td>0.540</td>
<td>0.536</td>
<td>0.582</td>
<td>0.654</td>
<td>0.484</td>
<td>0.550</td>
<td></td>
</tr>
<tr>
<td>ANN7</td>
<td>0.604</td>
<td>0.686</td>
<td>0.545</td>
<td>0.526</td>
<td>0.594</td>
<td>0.605</td>
<td>0.419</td>
<td>0.458</td>
<td></td>
</tr>
<tr>
<td>ANN8</td>
<td>0.591</td>
<td>0.674</td>
<td>0.571</td>
<td>0.509</td>
<td>0.665</td>
<td>0.727</td>
<td>0.443</td>
<td>0.412</td>
<td></td>
</tr>
<tr>
<td>ANN9</td>
<td>0.462</td>
<td>0.571</td>
<td>0.526</td>
<td>0.565</td>
<td>0.583</td>
<td>0.553</td>
<td>0.448</td>
<td>0.481</td>
<td></td>
</tr>
<tr>
<td>ANN10</td>
<td>0.481</td>
<td>0.523</td>
<td>0.540</td>
<td>0.600</td>
<td>0.600</td>
<td>0.487</td>
<td>0.496</td>
<td>0.481</td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.556</td>
<td>0.582</td>
<td>0.542</td>
<td>0.547</td>
<td>0.602</td>
<td>0.568</td>
<td>0.492</td>
<td>0.525</td>
<td></td>
</tr>
<tr>
<td>SD</td>
<td>0.056</td>
<td>0.071</td>
<td>0.016</td>
<td>0.059</td>
<td>0.033</td>
<td>0.078</td>
<td>0.064</td>
<td>0.098</td>
<td></td>
</tr>
</tbody>
</table>

Source: by the authors

In addition, to measure the importance of each predictor in the neural network, the normalized importance (%) shown in Table 9 was calculated using sensitivity analysis (Leong et al., 2019). The results show that PIQ is the most important predictor for ANN Model A with normalized importance at 100%, followed by SV (70%), UV (19.4%), and TSE (13.8%). For ANN Models B and C, the normalized importance is at 100% as there was only one neuron model in these ANN models. Next, for ANN Model D, ALO was the most important predictor with normalized importance at 100%, followed by the BOL factor with normalized importance at 48.7%. Finally, the results of comparing the difference in ratings between PLS-SEM and ANN revealed in Table 9 showed that all 4 models are consistent with the PLS-SEM results.
Table 9 Sensitivity Analysis

<table>
<thead>
<tr>
<th>Neural network</th>
<th>Model A (Output: OT)</th>
<th>Model B (Output: BOL)</th>
<th>Model C (Output: ALO)</th>
<th>Model D (Output: CVC)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UV</td>
<td>SV</td>
<td>PIQ</td>
<td>TSE</td>
</tr>
<tr>
<td>ANN1</td>
<td>0.123</td>
<td>0.306</td>
<td>0.352</td>
<td>0.219</td>
</tr>
<tr>
<td>ANN2</td>
<td>0.098</td>
<td>0.293</td>
<td>0.370</td>
<td>0.239</td>
</tr>
<tr>
<td>ANN3</td>
<td>0.152</td>
<td>0.255</td>
<td>0.415</td>
<td>0.178</td>
</tr>
<tr>
<td>ANN4</td>
<td>0.135</td>
<td>0.286</td>
<td>0.353</td>
<td>0.225</td>
</tr>
<tr>
<td>ANN5</td>
<td>0.203</td>
<td>0.298</td>
<td>0.283</td>
<td>0.216</td>
</tr>
<tr>
<td>ANN6</td>
<td>0.172</td>
<td>0.296</td>
<td>0.349</td>
<td>0.183</td>
</tr>
<tr>
<td>ANN7</td>
<td>0.135</td>
<td>0.233</td>
<td>0.403</td>
<td>0.228</td>
</tr>
<tr>
<td>ANN8</td>
<td>0.124</td>
<td>0.285</td>
<td>0.415</td>
<td>0.176</td>
</tr>
<tr>
<td>ANN9</td>
<td>0.225</td>
<td>0.226</td>
<td>0.316</td>
<td>0.233</td>
</tr>
<tr>
<td>ANN10</td>
<td>0.109</td>
<td>0.254</td>
<td>0.374</td>
<td>0.263</td>
</tr>
<tr>
<td>Average relative importance</td>
<td>0.148</td>
<td>0.273</td>
<td>0.363</td>
<td>0.216</td>
</tr>
<tr>
<td>Normalized relative importance (%)</td>
<td>19.400</td>
<td>70.000</td>
<td>100.000</td>
<td>13.800</td>
</tr>
</tbody>
</table>

Source: by the authors

Table 10 Comparison between PLS-SEM and ANN results

<table>
<thead>
<tr>
<th>PLS Path</th>
<th>Original Sample (O)/ Path Coefficient</th>
<th>ANN Results: Normalized Relative Importance (%)</th>
<th>Ranking (PLS-SEM) [Based on Path Coefficient]</th>
<th>Ranking (ANN) [Based on Normalized Relative Importance]</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model A (Output: OT)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>UV → OT</td>
<td>0.116</td>
<td>19.400</td>
<td>3</td>
<td>3</td>
<td>Match</td>
</tr>
<tr>
<td>SV → OT</td>
<td>0.303</td>
<td>70.000</td>
<td>2</td>
<td>2</td>
<td>Match</td>
</tr>
<tr>
<td>PIQ → OT</td>
<td>0.503</td>
<td>100.000</td>
<td>1</td>
<td>1</td>
<td>Match</td>
</tr>
<tr>
<td>TSE → OT</td>
<td>0.105</td>
<td>13.800</td>
<td>4</td>
<td>4</td>
<td>Match</td>
</tr>
<tr>
<td>Model B (Output: BOL)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OT → BOL</td>
<td>0.811</td>
<td>100.000</td>
<td>1</td>
<td>1</td>
<td>Match</td>
</tr>
<tr>
<td>Model C (Output: ALO)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OT → ALO</td>
<td>0.807</td>
<td>100.000</td>
<td>1</td>
<td>1</td>
<td>Match</td>
</tr>
<tr>
<td>Model D (Output: CVC)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BOL → CVC</td>
<td>0.371</td>
<td>48.700</td>
<td>2</td>
<td>2</td>
<td>Match</td>
</tr>
<tr>
<td>ALO → CVC</td>
<td>0.526</td>
<td>100.000</td>
<td>1</td>
<td>1</td>
<td>Match</td>
</tr>
</tbody>
</table>

Source: by the authors

4.2 DISCUSSION

By applying the theories of value co-creation, perceived value, and loyalty as the overall theoretical framework, this study has made some new findings regarding the formation of value co-creation between customers and AI chatbot service providers. It opens a broader view of customer behavior towards services and service providers after using AI chatbots through the impact factors of AI chatbots. Specifically, results from the study have shown that a positive perception of values from the two dimensions of utilitarian and social value, along with a positive perception of the information quality that AI chatbot brings to customers and the high technological self-efficacy of customers, will create online trust in AI chatbot for customers. This leads to the formation of their
loyalty in both behavioral and attitudinal aspects. From there, these two loyalty aspects will help businesses improve the level of customers' willingness to work with AI chatbot providers to create value co-creation. In short, the hypotheses proposed from this study are all supported by its experimental results except for the hedonic value. Simultaneously, the results of this research paper have contributed to exploring a new field in the context of AI chatbots that previous literature has rarely mentioned, that is the field of F&B.

4.2.1 Theory and Research Implications

This study contributes to the emerging literature regarding the use of AI chatbots by investigating the possibility of value co-creation between users and providers. First, while previous studies on AI chatbots have mainly focused on considering consumers' perceptions of satisfaction and intention to continue using (Ashfaq et al., 2020; Kwangsawad & Jattamart, 2022), the role of factors affecting AI chatbots in activating consumer participation in the co-creation of value is largely unknown. Therefore, the authors contributed to expanding the understanding of user behavior after using the AI chatbot service by establishing a theoretical relationship between dimensions of perceived value, perceived information quality, technological self-efficacy, and value co-creation via aspects of loyalty.

Second, in this study, the authors delved into the inside aspects of loyalty and divided loyalty into two main aspects behavioral and attitudinal to clarify their impact on the factors influencing AI chatbot and value co-creation. The results obtained from this study showed that both behavioral and attitudinal aspects of loyalty were determined by UV, SV, PIQ, and TSE. Also, the authors discovered that value co-creation can also be determined by behavioral loyalty and attitudinal loyalty in the AI chatbot context.

Finally, this study contributes to the previous literature with a more multidimensional perspective on theories when examining the effects of UV, HV, SV, PIQ, and TSE on BOL and ALO via OT. As a result, this study contributed to the literature regarding AI chatbots a new finding that consumers' hedonic value does not affect their online trust in forming consumer loyalty to AI chatbot services. While the remaining factors (UV, SV, PIQ, TSE) all have a strong influence on the formation of consumer loyalty via their online trust.
4.2.2 Practical Implications

To contribute to helping customers and businesses have a more comprehensive view of AI-based services, this study made the following contributions. First, the findings from this study show that businesses need to pay attention to factors related to utilitarian and social values when applying AI chatbot services to their business activities to create consumer trust in AI chatbot applications. Because when customers feel these values, they will become confident in the AI chatbot and are more likely to continue using or recommending this service to others. As a result, helping businesses build customer loyalty for their AI chatbot service. On the other hand, these findings also help customers have a clearer attitude in choosing and trusting a specific AI chatbot for long-term engagement and creating value co-creation.

Second, the results of this study indicate that businesses do not need to pay too much attention to hedonic value when building customer trust with the company's AI chatbot service. Instead, providers should focus more on upgrading the utilitarian and social values of AI chatbots for greater business efficiency and cost savings. This will help businesses create a sustainable competitive advantage based on creating the competitive advantage right from the development and launch of their AI chatbot (Hanifa et al., 2023). On the other hand, from the customer's perspective, this discovery helps customers have more confidence in their choices when they still decide to trust the AI chatbot they are using even though it's not satisfying or only partially satisfying customers' feelings about hedonic value.

Third, when developing AI chatbot-related service systems, service providers need to be careful in providing appropriate, highly accurate, consistent, and reliable information. Because this directly affects users' online trust in AI chatbots. Fourth, the findings show that training consumers to be more confident in themselves about using technology is also an inevitable factor contributing to building customer online trust in AI chatbots. On the other hand, when customers become aware of the correlation between technological self-efficacy and online trust, they will become more objective when evaluating a certain type of AI chatbot. Thereby providing customers with more correct beliefs when deciding to trust, be loyal, and work with AI chatbot providers to create value co-creation.

Finally, the findings of this study show that the customer's choice to participate in the co-creation of value is influenced by behavioral loyalty and attitudinal loyalty.
Therefore, to maintain and develop sustainably in today's competitive business environment, businesses need to build customer loyalty for their AI chatbot when deploying a new type of service such as an AI chatbot. Furthermore, customers becoming loyal and willing to create co-creating values also help customers create AI chatbots that suit their individual needs. From there, customers will feel more satisfied, and comfortable when using the AI chatbot service which they contribute to developing and improving it.

5 CONCLUSION

Firstly, this study was conducted by cross-sectional design. This has limited the ability to provide explanations for changes in user behavior over different periods. Therefore, the investigation of consumer behavior in the period when AI chatbot services have popular and gained consumer acceptance is necessary for future research. Nextly, the data of this study is only collected from a certain country, while the popularity of AI chatbot services in different countries is different. Moreover, the cultural, cognitive, and emotional factors of consumers in each country are also different. Hence, to understand the differences in consumer behavior in different countries when utilizing AI chatbot services, future studies may compare the model of this study in many various nations, including both developing and developed countries. Besides, online trust in this study is still a general variable and has not been fully exploited. Therefore, future studies may consider dividing online trust into different aspects (e.g., ability, benevolence, integrity, etc.) to gain a deeper understanding of the impact of different variables on online trust. Finally, it will be interesting if future studies focus on exploring the relationship between hedonic value and online trust at a time when AI chatbots have gained popularity among customers and businesses.

In summary, the increased use of innovative technologies helps businesses enhance their competitive advantage, facilitate the processing and analysis of large amounts of information, and interact more effectively with their customers (Bielialov et al., 2023). At the same time, this is also a key factor to help businesses improve service quality and position their brands more effectively (Chunikhina et al., 2023). Therefore, the authors hope that the findings from this study will have reference value for future researchers and service providers to devise marketing strategies to attract and retain customers.
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