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Consumer Propensity to Use Ai Chatbot in Purchase Decision Making from The Perspective of Valence Framework: The Role of Openness to Change and Compatibility

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Abstract

This research investigates consumers' inclination to utilize AI Chatbots for purchase decisions, employing the valence framework and examining the roles of Openness to Change and Compatibility. The study surveyed 320 chatbot users in the Sumbawa District. Findings reveal that Openness to Change significantly influences chatbot users' purchasing decisions within the valence framework context, encompassing both Perceived Benefit and Perceived Risk. This highlights the crucial role of Openness to Change in understanding consumer behavior, as it can substantially impact decisions regarding chatbot usage when considering perceived benefits and risks. The research also confirms the positive effects of chatbot utilization. By incorporating Openness to Change and Compatibility, the study offers a novel perspective on chatbot usage in purchasing decisions. This approach distinguishes the research, as it applies the valence framework (Perceived Benefit and Perceived Risk) to chatbot usage while introducing the additional dimensions of Openness to Change and Compatibility.

Keywords: *Chatbot, Purchase Decision, Valence Framework*

INTRODUCTION

In today's digital marketing landscape, chatbots are emerging as a pivotal strategy for businesses adapting to the evolving digital service environment. Within the marketing sphere, chatbots serve five essential functions: interaction, entertainment, trendiness, customization, and problem-solving. These functions are intricately tied to enhancing customer engagement. As one of the most in-demand online business tools in the digital age, chatbots have garnered significant attention. This has prompted both researchers and companies to harness information and communication technology to enhance online services and mobile applications. The applications of chatbots span a wide range of sectors, including: Hotel reservations, Flight bookings, Food ordering, Product and service inquiries, Travel guidance, Customer support and issue resolution. By integrating chatbots into these areas, businesses are streamlining their operations and improving customer experiences. This technological adoption reflects the growing importance of AI-driven communication in meeting consumer needs and expectations in the digital marketplace (Følstad et al., 2018), (Um et al., 2020) and (Ukpabi et al., 2019).

Chatbots are innovative software applications engineered to simulate human conversation. They employ natural language processing to enhance the interaction between humans and technology (Kwangsawad & Jattamart, 2022). The deployment of chatbots for real-time communication with users about products and services is gaining significant traction (Luo et al., 2019). One of the key advantages of chatbots lies in their simplicity and flexibility. These qualities enable them to provide valuable support to both end users and businesses alike (Przegalinska et al., 2019). As chatbots become more ubiquitous in various sectors, there's a growing emphasis on two critical aspects: User satisfaction, Users' willingness to adopt and engage with chatbot technology. This increased focus reflects the importance of understanding and improving the user experience with chatbot interactions (Rese et al., 2020). The rise of chatbots represents a significant shift in how businesses and

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consumers interact in the digital space. As this technology continues to evolve, it's becoming increasingly important to study its impact on user experience and adoption rates, ensuring that chatbots effectively meet the needs of both businesses and their customers.

The chatbot market is experiencing significant growth, with projections indicating an increase from $2.6 billion in 2019 to $9.4 billion by 2026. Customer service remains the primary driver of this expansion (Chakrabortty et al., 2023). As of 2018, Facebook Messenger alone hosted approximately 300,000 active chatbots (Rapp et al., 2021). Industry forecasts suggested that by 2022, chatbots would handle 85% of all customer service interactions (Grudin & Jacques, 2019). The rapid evolution of the chatbot industry, coupled with intense business competition, is significantly impacting service delivery methods and consumer interest in chatbot-related products. Research has validated various aspects of consumer behavior in relation to chatbot usage, including satisfaction, convenience, loyalty, and purchase intention (Talwar et al., 2020). Purchase intention stands out as a critical factor influencing consumer buying behavior. Previous studies have also highlighted the role of demographics, perceived risk, attitude, and compatibility in shaping purchase intentions (Amaro & Duarte, 2015). This growth trajectory underscores the increasing importance of chatbots in modern business operations, particularly in enhancing customer service experiences and influencing consumer purchasing decisions. As the technology continues to evolve, it's likely to play an even more significant role in shaping consumer interactions and business strategies across various industries.

Perceived capability refers to the mental process through which users recognize potential actions when interacting with objects. In the context of chatbots, if they provide an efficient means for customers to achieve their goals, such as acquiring desired information, the chatbot's functional features create opportunities for customer engagement (Li et al., 2023) . (Holzwarth et al., 2006) emphasized that the primary purpose of implementing chatbots is to effectively meet customer needs. When this objective is achieved, it results in several positive outcomes: Favorable attitudes towards the brand or service, Increased purchase intentions, Enhanced customer loyalty, Collectively, these outcomes contribute to overall customer satisfaction. In essence, the effectiveness of chatbots in fulfilling customer requirements plays a crucial role in shaping user perceptions and behaviors. When chatbots successfully meet user needs, they not only improve the immediate interaction but also positively influence broader aspects of the customer-business relationship. This underscores the importance of designing and implementing chatbots that are truly capable of understanding and addressing customer needs efficiently and effectively.

The competitive advantage theory posits that one effective strategy for creating superior value is to enhance marketing innovation through technological adoption (Um et al., 2020). This approach emphasizes the importance of leveraging technology, such as chatbots, to gain a competitive edge in the market. On the other hand, consumer value theory suggests that several factors influence purchasing decisions when it comes to chatbot usage (Misischia et al., 2022). In essence, the integration of chatbots in business strategies aligns with both competitive advantage theory and consumer value theory. By offering enhanced customer experiences through technological innovation, businesses can create superior value. Simultaneously, by addressing key factors that influence consumer decision-making, chatbots can effectively guide and influence purchasing behaviors. This dual approach underscores the potential of chatbots as powerful tools in modern marketing and customer service strategies.

When consumers interact with chatbots, their purchasing decisions are significantly influenced by perceived benefits such as accurate pricing information, product quality details, service quality, and overall effectiveness. Additionally, the convenience of using chatbots, references obtained from chatbot interactions, and comparative information provided also play a role in shaping purchasing choices (Holzwarth et al., 2006). However, this perspective overlooks the crucial role of personality traits in consumer behavior and decision-making. Consumer behavior is generally considered more effective than demographic factors in explaining purchasing decisions (Chakrabortty et al., 2023). To address this gap, we've developed a comprehensive framework that incorporates individual traits, perceptions, and purchase intentions. This approach allows us to examine how various emotions impact the decision to use chatbots for making purchases. Our study employs a valence framework to assess both positive and negative consumer perceptions, providing a more holistic understanding of the reasoning behind purchase decision-making in the context of chatbots. Compared to other behavioral frameworks, the valence framework is more adept at explaining variations as it simultaneously considers perceived benefits and risks (Ngoc et al., 2024).

Furthermore, consumer characteristics such as openness to change and adherence to norms have been widely used in numerous studies to elucidate consumer behavior in purchasing decisions (Hansen et al., 2018). However, these characteristics have not been thoroughly explored in the context of chatbot usage. Therefore, we've chosen to utilize a valence framework, integrating openness to change and compatibility as personal traits. This approach allows us to establish correlations between consumers' positive perceptions, negative perceptions, and purchase decision-making among chatbot users, providing a more comprehensive understanding of consumer behavior in this emerging technological context.

The remaining sections of the article will unfold as follows: Initially, I'll outline research hypotheses and a theoretical framework drawn from the literature. Next, I'll delve into the research methodology. Following that, I'll unveil our findings and compare them with previous research outcomes. Lastly, I'll wrap up by discussing the study's contributions and limitations, along with offering recommendations for future research endeavors.

LITERATURE REVIEW

Openness to Change

Openness to change refers to an individual value that stimulate and encourage a person to engage to an action independently (Yeh & Harmel, 2018). Prior studies have explored the correlation between Openness to change and consumers behaviors in various context. (Claudy et al., 2015) argued that Openness to change has positive relation with acceptance reasons and negative relation to reasons to resist the implementation of wind turbines and car-sharing services. Likewise, (Eri et al., 2024) argued that Openness to change respectively has favorable connection with reasons to use, and negative connection with reasons to oppose using wearable devices based on internet-of-things (IOT) for elderly healthcare. (Piscicelli et al., 2015) reported that users with higher value of Openness to change are more likely to engage to cooperative consumer behaviors such as: sharing, borrowing, exchanging, gifting, and lending. Similarly (Hansen et al., 2018) observed that as the value of openness to change increases, consumers are more likely to make a purchase decision. Building on previous research findings, we suggest that openness to using chatbots could positively influence perceived benefits and negatively impact perceived risks. Therefore, the hypothesis is as follows:

H1: There is a positive relationship of openness to the use of chatbot

H2: There is a positive relationship between Openness to Change to Perceived Benefit through Use of Chatbot

H3: There is a positive relationship between Openness to Change to Perceived Risk through Use of Chatbot.

H4: There is a positive relationship between Use of Chatbot and Purchase Decision from the perspective of Perceived Benefit with the role of Openness to Change.

H5: There is a positive relationship between Use of Chatbot and Purchase Decision from the perspective of Perceived Risk with the role of Openness to Change.

H6: There is a positive relationship between Openness to Change and Purchase Decision through Use of Chatbot.

Compatibility

Compatibility refers to the extent to which a change aligns with consumers' previous experiences, trust, and sociocultural values. (Rogers et al., 2019) Likewise, (Bunker et al., 2007) It has been established that compatibility entails an innovation meeting the values and standards of consumers. Compatibility is recognized as a crucial factor that influences consumers' acceptance of innovation (Dhir et al., 2021). In the study of purchasing decision-making (Omarov et al., 2022) The study discovered that the adaptation of chatbot usage influences purchasing decisions through customization. The study suggests that when a product or service aligns with a person's lifestyle, the perceived risk associated with that product is reduced, leading consumers to feel more secure (Giovanis et al., 2012). Additionally, the research confirms that compatibility has a positive influence on consumers' perceived practical value and convenience. Furthermore, (Jain & Owusu-Ansah, 2023) the research also affirms that compatibility will positively influence the adaptability of using a chatbot, thereby impacting consumer purchase decision-making. Consistent with prior studies, we posit that compatibility will have a positive effect on the perceived benefits of chatbot users. Additionally, chatbot users will also influence consumers' purchase decision-making. Therefore, the proposed hypothesis is as follows:

H7: There is a negative relationship of compatibility to the use of chatbot

H8: There is a negative relationship between Compatibility to Perceived Benefit through Use of Chatbot

H9: There is a negative relationship between Compatibility to Perceived Risk through Use of Chatbot

H10: There is a positive relationship between Use of Chatbot and Purchase Decision from the perspective of Perceived Benefit with the role of Compatibility.

H11: There is a positive relationship between Use of Chatbot and Purchase Decision from the perspective of Perceived Risk with the role of Compatibility.

H12: There is a negative relationship between Compatibility and Purchase Decision through Use of Chatbot

The Valence Framework

The valence framework examines how the emotional positivity or negativity of an experience influences consumers' willingness to engage in consuming a product, service, or taking a specific action (S. A. Khan et al., 2015). The valence framework has demonstrated its effectiveness in elucidating individual decision-making by encompassing both positive and negative valence. Through the consideration of both perceived benefits and perceived risks, this framework provides a more comprehensive explanation of variances compared to other behavioral theories (Ngoc et al., 2024). Therefore, the valence framework offers a more comprehensive explanation of an individual's intention to take a particular action by encompassing both the positive and negative effects on the action (S. A. Khan et al., 2015). (Ozturk et al., 2017) The perceived benefit in the valence framework comprises two primary elements: convenience and utilitarian value. Convenience refers to the time and effort needed to participate in an action, while utilitarian value denotes the acknowledged functional attributes (Han et al., 2017). On the other hand, Perceived risk is characterized as the uncertainty and potential negative outcomes associated with consumers engaging in a particular action (Ozturk et al., 2017).

Certain academics have also employed the valence framework to elucidate consumer acceptance (Lu et al., 2011) This framework was employed to investigate the factors that encourage and impede consumers' inclination to utilize online banking services. (He et al., 2018) The study confirmed that Positive Utility encompasses Perceived Monetary benefit and Perceived Symbol, while Negative Utility comprises Perceived risk and Perceived Fee. Both positive and negative utilities significantly influence consumer intention to purchase electric vehicles. (Xiao et al., 2021) In examining the intention to use online healthcare services, the positive utility was defined as Social support, Financial, Convenience, and Utilitarian value, whereas the negative utility encompassed Social risk, Physical risk, and Privacy risk. Furthermore, based on this framework, (Dhir et al., 2021) Additionally, an expanded model was formulated to assess the willingness of Japanese consumers to recycle electronic waste. Following the aforementioned research, we have also employed the Valence framework to elucidate consumer purchasing decisions regarding the use of chatbots. This approach considers the perceived benefits and risks by consumers. The perceived benefits act as a driver for consumers to engage with chatbots, as it focuses on comparing the value gained from using chatbots against the perceived risks stemming from the openness of internet technology infrastructure. Consumers express concerns about information security, privacy, and associated risks.

Perceived Benefit

Perceived benefit represents favorable incentives when consumers consider using or selecting a product or service (Elhoushy et al., 2020). The perceived benefit is a key component of the valence framework, serving to motivate an individual to engage in a particular action. This perceived benefit encompasses more than just financial gain and encompasses a broad spectrum of factors that offer advantages throughout the purchasing process (Mai et al., 2022). In the context of chatbot usage, perceived benefit refers to the extent to which consumers believe they will gain from using a chatbot. These perceived benefits encompass various aspects, such as utilitarian value and convenience. Utilitarian value represents the consumer's assessment of the practical attributes of an action (Han et al., 2017).

Convenience is the acknowledgment of the usefulness that minimizes the time and effort required by a consumer when purchasing or using a product or service (Berry et al., 2002). Consumers benefit from the ease and speed of conducting various actions and transactions over the internet (Han et al., 2017). Moreover, consumers can enjoy a multitude of advantages, including competitive pricing resulting from fierce online competition, streamlined transactions, all of which can influence their purchasing decisions (Grudin & Jacques, 2019). (Gkinko & Elbanna, 2023) found that there is a positive relationship between the correlation between the use of chatbots and consumer purchasing decisions, in another study (Brachten et al., 2021) It seems that the provided Web Search Results are not directly related to a specific research study on the factors influencing purchasing decisions and the perceived benefits of chatbot usage by consumers. If you have a specific research study in mind, please provide the details, and I can assist in summarizing or analyzing it based on the information available (Xiao et al., 2021) The research indicates that perceived utility, encompassing social support, convenience, and satisfaction value, significantly impacts consumers' purchasing decision-making. Consequently, we argue that consumers' perceived benefits from using a chatbot play a crucial role in influencing their purchasing decisions. These perceived benefits comprise, among other factors, the convenience and practical value of using a chatbot compared to a traditional service provider. Therefore, consumers with a higher perceived value of benefits are expected to have a more logical rationale for making purchases, leading to improved decision-making. Hence, the hypothesis is as follows:

H13: There is a positive relationship of Perceived Benefit on Purchase Decision

Perceived Risk

As one of the two essential components of the valence framework, perceived risk, in contrast to perceived benefit, adversely influences consumer behaviors. Consumers' apprehension regarding the outcomes of using a product or service is referred to as perceived risk (Martins et al., 2014). (Kim et al., 2008) It is anticipated that the perceived risk is the belief regarding the likelihood of unfavorable outcomes occurring when acquiring a product or service. This was explored in their research on the adoption of new technology (Cocosila & Trabelsi, 2016) The research discovered that various forms of risk, such as time consumption, financial risk, physical risk, and social risk, have discouraged individuals from utilizing mobile payment systems. In online purchasing, perceived risk, delivery processes, technological understanding, the risk of divulging personal and financial information, lack of interpersonal contact, and personal connection are factors that are seen as risky, thereby reducing the likelihood of users making a purchase (Tandon et al., 2017). Therefore, in various scenarios, the perceived risk may be influenced by different factors.

In the context of using chatbots, perceived risk refers to consumers' perceptions of potential negative outcomes and uncertainty associated with interacting with chatbots (Chen & Kuo, 2017). While using a chatbot, consumers encounter the inherent risks of online transactions and information searches related to purchasing, with privacy and security risks being the most significant among them (Lee & Hwang, 2017). In addition, (Bell & Bryman, 2007) The research supported their findings that vulnerability barriers are indeed a form of risk in the context of consumer behavior when making online purchasing decisions. Additionally, other studies have highlighted privacy and security concerns regarding the collection of personal information by chatbot providers (Gao et al., 2015).

Vulnerability barriers assess the utilization of chatbots, indicating that their capabilities are constrained by the internet connectivity provided by the service provider. (Li et al., 2023). (Kim et al., 2008) It was found that the perception of risk does indeed have adverse effects on the intention to carry out online transactions. Other research results (Lu et al., 2011) The research also corroborates the existence of an adverse correlation between perceived risk and consumer behavior when making purchasing decisions. However, the study also indicates that negative reports play a moderating role in the relationship between perceived risk and consumer behavior, particularly in cross-platform purchasing behavior. (Talwar et al., 2020) This paper presents contrasting findings, as it suggests that perceived risk has a positive influence on consumer behavior for purchase decision making. The study aims to provide further insights into this relationship. Additionally, when utilizing a chatbot, users need to register by supplying personal information, which can elevate the perceived risk when consumers acknowledge that the data provided during chatbot registration could increase potential risks. Accordingly, the hypothesis is developed as below:

H14: There is a negative relationship between Perceived Risk and Purchase Decision

Chatbot

A Chatbot is a computerized system that replicates human conversation through text or voice messages. The pioneer in this field is ELIZA, created by MIT professor Joseph Weizenbaum in 1966. Initially, conversations relied on matching sentence patterns with predefined responses. Through the integration of natural language processing (NLP) and learning from artificial intelligence (AI), chatbots have evolved to become more user-friendly (Um et al., 2020). The human-like characteristics of chatbots can help foster confidence and emotional rapport between customers and technology. Therefore, in order to efficiently deploy chatbot applications, it is essential to comprehend the significance of user trust in chatbot applications, along with their precursors and behavioral consequences (Alagarsamy & Mehrolia, 2023). Empirical analysis has confirmed the potential enhancement of a hotel organization's performance through the introduction of chatbots (Prentice et al., 2020).

The existing literature on the use of chatbots in influencing consumer purchase decisions is fairly extensive (Alagarsamy & Mehrolia, 2023) and (Wang et al., 2022). These studies individually examine specific aspects that can impact consumer purchase decisions resulting from the use of chatbots. Thus, it is apparent that none of the studies have considered a model that can concurrently evaluate both positive and negative perceptions of chatbot use influencing consumer purchase decisions. Such a comprehensive framework would provide a more thorough explanation of consumer perceptions within the context of chatbot usage. Moreover, commonly used consumer traits such as openness to change and agreeableness, which are significant in interpreting consumer behavior related to purchase decision-making, have not been taken into account in the context of chatbot use. Essentially, previous research overlooked the significance of variations in consumers' personal traits and failed to simultaneously consider both positive and negative perceptions. To address this gap, the authors formulated a framework for personality traits, perceptions, and consumer purchase decision-making to better investigate how distinct perceptions and emotions impact consumer purchase decision-making resulting from chatbot usage, Hence, the hypothesis is as follows:

H15: There is a positive relationship of Use of Chatbot on Perceived Benefit

H16: There is a positive relationship Use of Chatbot on Perceived Risk

H17: There is a positive relationship between Use of Chatbot and Purchase Decision

H18: There is a positive relationship between Use of Chatbot and Purchase Decision through Perceived Benefit

H19: There is a positive relationship between Use of Chatbot and Purchase Decision through Perceived Risk

In the introduction, it was pointed out that the examination of how chatbots impact consumer buying choices can be approached through The Valence Framework. This involves considering the influence of Openness to Change and Compatibility. This led me to suggest a theoretical model, as depicted below.

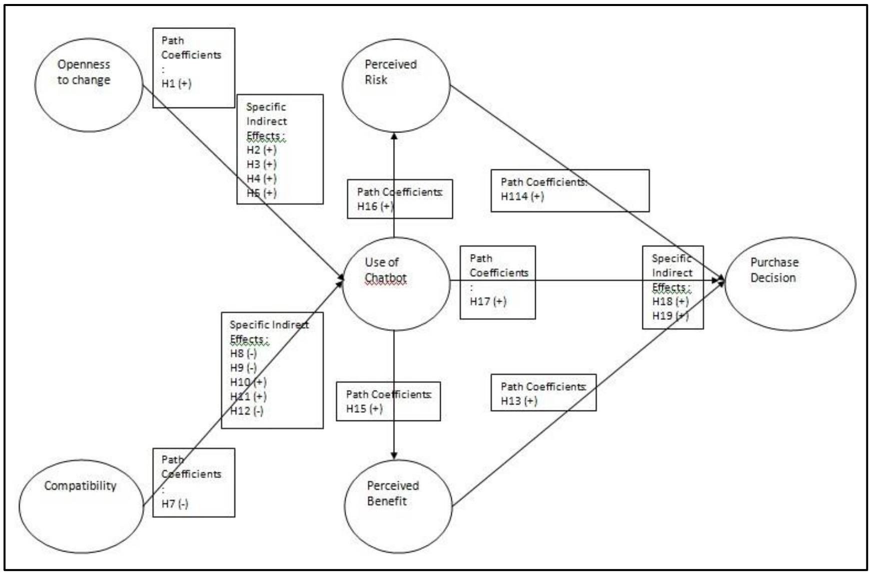

Fig. 1. Proposed research model.

METHODOLOGY

This research incorporates six measurement constructs, including perceived benefits and perceived risks, which are key components of the valence framework. Notably, many of these constructs have been insufficiently explored in previous studies examining chatbots' impact on consumer purchasing decisions from a valence framework perspective, particularly regarding the roles of openness and compatibility variables in chatbot usage. Previous studies have typically adopted measurement scales from similar contexts. For instance, (Khoa, 2021) investigated chatbot use in consumer decision-making, highlighting parallels in technology adoption advantages via chatbots, such as ease of use and perceived benefits in online purchasing and information retrieval. To ensure contextual appropriateness, a comprehensive methodology was employed, as recommended by (McMillan & Hwang, 2002), incorporating literature review, open-ended interviews, structured interviews, and cross-sectional surveys.

The study targets individuals aged 18 and above who use both text-based and voice-based chatbots for online shopping within the Sumbawa District. Cross-sectional data was collected directly through questionnaires to ensure precision and completeness. Sample allocation was based on gender, age, profession, and income criteria. A total of 320 chatbot users in the Sumbawa District participated in the survey, conducted from March 22 to April 21, 2023. All respondents received the same set of questions in a predetermined sequence. Survey methodology facilitates widespread distribution, resulting in a sample suitable for broader population generalizations. Surveys also offer faster and more cost-effective data collection compared to methods like interviews, with reduced likelihood of interviewer bias (Jain & Owusu-Ansah, 2023). The study employed statistical methods to assess causal relationships and predictive capabilities, utilizing Structural Equation Modeling (SEM) based on the Partial Least Squares (PLS) method. This approach allows evaluation of both direct and indirect (mediated) relationships among variables of interest. PLS-SEM is widely used across various disciplines for analyzing causal relationships among latent variables (Hair et al., 2015). This method verifies the significance of both direct and mediated relationships (Nitzl et al., 2016);(Sarstedt et al., 2019); (Kusa, 2023). The analysis was conducted using SmartPLS software version 3.2.9. This comprehensive approach ensures a robust methodology for examining the complex relationships between chatbot usage, consumer perceptions, and purchasing decisions, while addressing gaps in previous research and providing a solid foundation for generalizable insights.

DISCUSSION OF RESULTS

To ascertain the accuracy of the proposed indicators in measuring constructs, it is crucial to evaluate the reliability and validity of the measurement model, as outlined by (Klarner et al., 2013). The results of this assessment are presented in Tables 2, 3, and 4.

Table 2. Construct reliability and validity

Research constructs	Item	Outer loadings	VIF	Cronbach's alpha	CR	AVE
Openness to Change	OC1. I am constantly seeking new and surprise thing in my life.	0.792	1.110	0.679	0.793	0.657
	OC2. I'm looking for discovery and adventure.	0.828	1.110			
Compatibility	CO1. Using Chatbot is suitable with my demand.	0.975	1.369	0.683	0.832	0.718
	CO2. Using Chatbot is compatible with my shopping approach	0.696	1.369			
Use of Chatbot	UC1. I found it easy to become skilled in using the Chatbot.	0.712	1.081	0.629	0.773	0.632
	UC2. My interactions with the Chatbot assistant were clear and easy to understand.	0.870	1.081			
Perceived Risk	PR1. I'm worried that using a chatbot will make my life wasteful.	0.902	1.381	0.689	0.864	0.761
	PR2. I am concerned that the data shared with the chatbot will be shared with third parties.	0.841	1.381			
Perceived Benefit	PB1. The chatbot helps me save time and effort	0.773	1.220	0.656	0.706	0.706
	PB2. a chatbot will help me complete my purchase quickly.	0.903	1.220			
Purchase Decison	PD1. A chatbot can influence my purchase decision.	0.875	1.033	0.643	0.583	0.583
	PD2. The chatbot helped me with the price comparison of the items.	0.633	1.033			

Source: Authors calculated using SmartPLS 3.2.9.

To gauge reliability and construct validity, I employed Cronbach's alpha and composite reliability, with Table 2 detailing the findings. According to (Kock, 2014), a threshold of 0.7 is deemed acceptable for these metrics. Out of the six constructs examined, two exhibit values exceeding this threshold, indicating adequacy in their construction. Despite Cronbach's alpha for Compatibility (Co2) and Purchase Decision (PD2) slightly dipping below 0.7, (Hair et al., 2015) advocate for an acceptable level of 0.6 for Cronbach's alpha. Therefore, I argue that these two constructs demonstrate internal consistency, especially considering their composite reliability values, which significantly surpass the recommended threshold for acceptability as outlined by (Netemeyer et al., 2003).

Table 2 also exhibits the outer loadings of each latent variable alongside their corresponding average variance extracted (AVE). According to the Partial Least Squares Structural Equation Modeling (PLS-SEM) methodology, the expected loading value is 0.7, with 0.5 considered acceptable (Ketchen, 2013). Only two outer loadings for the Compatibility (CO_2) and Perceived Risk (PR_3) constructs slightly fall below the 0.7 threshold, suggesting that all indicators can be deemed significant. Furthermore, the AVE values for all constructs exceed 0.5, confirming the relevance of all variables considered (Kock, 2015).

To ascertain the absence of collinearity issues among the indicators within each construct, I utilized the variance inflation factor (VIF). According to the research by (Diamantopoulos & Siguaw, 2006), collinearity problems are improbable if VIF values stay below 3.30. The data presented in Table 2 validates that all items complied with this criterion.

Table 3. Heterotrait-Monotrait Ratio Criteria.

Concepts	Compatibility	Openness to Change	Perceived Benefit	Perceived Risk	Purchase Decison	Use of Chatbot
Compatibility						
Openness to Change	0.801					
Perceived Benefit	0.351	0.020				
Perceived Risk	0.084	0.898	0.390			
Purchase Decison	0.637	0.390	0.792	0.626		
Use of Chatbot	0.314	0.196	0.860	0.418	0.502	

Source: Authors calculated using SmartPLS 3.2.9.

Table 4. Fornell-Larcker Criterion.

Concepts	Compatibility	Openness to Change	Perceived Benefit	Perceived Risk	Purchase Decison	Use of Chatbot
Compatibility	**0.847**					
Openness to Change	0.471	**0.811**				
Perceived Benefit	0.300	0.554	**0.840**			
Perceived Risk	0.669	0.497	0.250	**0.872**		
Purchase Decison	-0.274	-0.538	-0.470	-0.326	**0.764**	
Use of Chatbot	-0.191	-0.542	-0.462	-0.207	0.551	**0.795**

Source: Authors calculated using SmartPLS 3.2.9.

Ensuring the validity of the model entails assessing the discriminant (differential) validity of the constructs, as emphasized (Kock, 2015). I conducted this assessment using the Fornell-Larcker criterion and the heterotrait-monotrait coefficient (HTMT). According to (Fornell & Larcker, 1981) and (Kock, 2015), discriminant validity is achieved when the square root of the average variance extracted (AVE) exceeds the correlation with other constructs in the model. Conversely, as indicated by (Henseler et al., 2016), discriminant validity is established if the HTMT coefficient remains below 0.85 for latent variables. The results of the discriminant validity analysis, presented in Tables 3 and 4, illustrate that all examined constructs demonstrate differential validity.

Moreover, the square root of the average variance extracted (AVE) for each construct surpasses the other correlation coefficients listed in Table 3, which aligns with recommended practices. The HTMT values presented in Table 3 are below 0.9, consistent with the guideline proposed by (Henseler et al., 2016). The bootstrap analysis verified that the HTMT confidence intervals, spanning from 2.5% to 97.5%, do not encompass 1, indicating precision. Consequently, the calculated discriminant values adhere to the specified criteria. Following the guidelines outlined by (Hair et al., 2015), the assessment of discriminant validity entails evaluating cross-load coefficients, the Fornell-Larcker criterion, and the heterotrait-monotrait ratio (HTMT). The results indicate that the cross-loadings of the observed variables within each construct surpass those observed in other constructs.

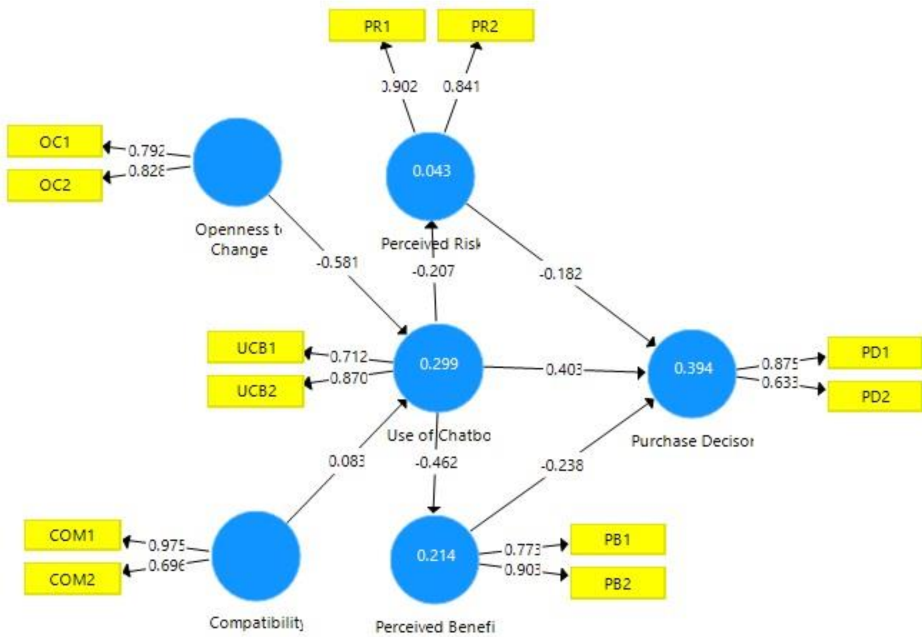

Fig. 2. Theoretical model analysis results using PLS-SEM.

Source: Authors calculated using SmartPLS 3.2.9.

Table 5. Result for Path Coefficients.

<table>
<tr><th rowspan="2">HypoHypothesis</th><th rowspan="2">Path Coefficients</th><th colspan="5">Bootstrapping</th></tr>
<tr><th>Original Sample (O)</th><th>Sample Mean (M)</th><th>Standard Deviation (STDEV)</th><th>T Statistics (|O/STDEV|)</th><th>P Values</th></tr>
<tr><td>H1</td><td>Openness to Change -> Use of Chatbot</td><td>-0.581</td><td>-0.574</td><td>0.052</td><td>11.248</td><td>0.000</td></tr>
<tr><td></td><td>Specific Indirect Effects</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>H2</td><td>Openness to Change -> Use of Chatbot -> Perceived Benefit</td><td>0.269</td><td>0.267</td><td>0.038</td><td>7.150</td><td>0.000</td></tr>
<tr><td>H3</td><td>Openness to Change -> Use of Chatbot -> Perceived Risk</td><td>0.121</td><td>0.122</td><td>0.036</td><td>3.388</td><td>0.001</td></tr>
<tr><td>H4</td><td>Openness to Change -> Use of Chatbot -> Perceived Benefit -> Purchase Decison</td><td>-0.064</td><td>-0.063</td><td>0.016</td><td>4.048</td><td>0.000</td></tr>
<tr><td>H5</td><td>Openness to Change -> Use of Chatbot -> Perceived Risk -> Purchase Decison</td><td>-0.022</td><td>-0.023</td><td>0.011</td><td>2.089</td><td>0.037</td></tr>
<tr><td>H6</td><td>Openness to Change -> Use of Chatbot -> Purchase Decison</td><td>-0.235</td><td>-0.230</td><td>0.046</td><td>5.059</td><td>0.000</td></tr>
<tr><td>Hypothesis</td><td>Path Coefficients</td><td>Original Sample (O)</td><td>Sample Mean (M)</td><td>Standard Deviation (STDEV)</td><td>T Statistics (|O/STDEV|)</td><td>P Values</td></tr>
<tr><td>H7</td><td>Compatibility -> Use of Chatbot</td><td>0.083</td><td>0.062</td><td>0.059</td><td>1.407</td><td>0.160</td></tr>
</table>

	Specific Indirect Effects					
H8	Compatibility -> Use of Chatbot -> Perceived Benefit	-0.038	-0.029	0.028	1.373	0.170
H9	Compatibility -> Use of Chatbot -> Perceived Risk	-0.017	-0.013	0.012	1.407	0.160
H10	Compatibility -> Use of Chatbot -> Perceived Benefit -> Purchase Decison	0.009	0.007	0.007	1.377	0.169
H11	Compatibility -> Use of Chatbot -> Perceived Risk -> Purchase Decison	0.003	0.002	0.002	1.275	0.203
H12	Compatibility -> Use of Chatbot -> Purchase Decison	0.033	0.026	0.026	1.299	0.195
Hypothesis	Path Coefficients	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H13	Perceived Benefit -> Purchase Decison	-0.238	-0.238	0.053	4.449	0.000
H14	Perceived Risk -> Purchase Decison	-0.182	-0.189	0.065	2.803	0.005
H15	Use of Chatbot -> Perceived Benefit	-0.462	-0.464	0.042	10.930	0.000
H16	Use of Chatbot -> Perceived Risk	-0.207	-0.211	0.053	3.879	0.000
H17	Use of Chatbot -> Purchase Decison	0.403	0.399	0.066	6.140	0.000
	Specific Indirect Effects	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
H18	Use of Chatbot -> Perceived Benefit -> Purchase Decison	0.110	0.110	0.025	4.343	0.000
H19	Use of Chatbot -> Perceived Risk -> Purchase Decison	0.038	0.040	0.018	2.148	0.032

Source: Authors calculated using SmartPLS 3.2.9.

The iterative bootstrapping process, conducted over 5000 iterations, enabled me to assess the statistical significance of the path coefficient estimates, employing a two-sided test with a critical probability of 0.05. As detailed in Table 5, it becomes evident that only the Compatibility variable lacks a significant impact on the Use of Chatbot, both within the framework of the valence perspective and its influence on Purchase Decision. This observation is supported by the Path Coefficients test results. Additionally, Specific Indirect Effects (H8: P Values, 0.160 > 0.05), (H9: P Values, 0.170 > 0.05), (H10: P Values, 0.169 > 0.05), (H11: P Values, 0.203 > 0.05), and (H12: P Values, 0.195 > 0.05) all align with this conclusion. Field analysis also highlights the challenges faced by chatbot users in the Sumbawa sub-district, particularly concerning limited internet access and disparities in making purchasing decisions. This suggests that while the chatbot user community in Sumbawa sub-district displays interest in products, direct purchases are hindered by anticipation of future income. This echoes findings by (Jan et al., 2023), indicating that internet accessibility significantly impacts chatbot usage, while purchasing decisions are influenced by economic factors (Kholis & Ma'rifa, 2021).

Conversely, the impact of the Use of Chatbot variable on Purchase Decision is notably positive (P Values, 0.000 < 0.05) (H17), indicating that chatbot users in Sumbawa District recognize the utility of chatbots in the digital age for swift and cost-effective information retrieval, even for essential needs, as underscored by (Borde Associate Professor et al., 2023).

At first, the analysis of Specific Indirect Effects reveals that the Openness to Change element substantially contributes to the advantages derived from utilizing Chatbots (H1) among users within the chatbot community of Sumbawa District. Moreover, the utilization of Chatbots can significantly influence purchasing decisions through the lens of benefits (H2), which includes providing up-to-date product information and the time-saving aspect acknowledged by chatbot users (Ukpabi et al., 2019); (Sheehan et al., 2020). However, conversely, the widespread use and reliance on chatbots in various purchasing activities raise concerns regarding potential breaches of customer data privacy (H16) (Saputra & Sutarso, 2024); (A. F. Khan & Chawla, 2014); (Tran et al., 2021).

Secondly, the study outcomes underscore that the principal factors supporting consumer purchasing decisions facilitated by chatbots are the openness factor and the benefits derived from utilizing chatbots in purchasing decisions (H3, H4, H5, and H6). Empirical evidence highlights the significance of the benefits of using chatbots, particularly due to the role of the openness factor, which influences consumer purchasing decisions. This is in contrast with previous studies where consumers predominantly relied on traditional methods for purchasing decisions (Hong et al., 2023). Essentially, when chatbot users in Sumbawa Sub-district perceive chatbot services as more beneficial in terms of time and cost, it significantly affects their purchasing decisions, making them more inclined to utilize chatbots.

Moreover, this study affirms that Compatibility exerts a negative influence on the benefits derived from utilizing chatbots (H7), as well as on the risks associated with their use (H9). Additionally, Compatibility's role in influencing purchasing decisions, both in terms of the benefits accrued from using chatbots (H8) and the perceived risks (H11), is examined. Notably, Compatibility's impact on purchasing decisions stemming from chatbot usage (H12) is deemed insignificant (P Values > 0.05), findings corroborated by research (Talwar et al., 2020).

On one hand, these findings contradict previous research by (Kim et al., 2008), (Alagarsamy & Mehrolia, 2023), (Saputra & Sutarso, 2024), and (Asgarpour et al., 2014), which assert that perceived risk negatively influences online purchasing decisions via chatbots. Finally, the study underscores the pivotal role of the Openness to Change factor in shaping purchasing decisions through chatbot usage, emphasizing the perceived benefits by chatbot users. However, it also acknowledges the risk factor associated with chatbot usage, particularly concerning the significance of consumer data in every account use (Illescas-Manzano et al., 2021).

CONCLUSION

This study investigates consumers' inclination to use AI Chatbots in purchasing decisions, employing the valence framework and examining the influence of Openness to Change and Compatibility. The key findings are: (1) Openness to Change significantly impacts chatbot users' purchasing decisions within the valence framework (Perceived Benefit and Perceived Risk). This highlights its crucial role in understanding consumer behavior, as it can notably influence decisions regarding chatbot usage in the context of perceived benefits and risks. (2) The results affirm the positive effects of chatbot utilization.(3) Compatibility fails to demonstrate a significant explanatory effect on purchasing decisions within the valence framework for chatbot users. These findings suggest that certain limitations, such as unstable internet connectivity in local areas and the confined user base of chatbots to specific demographics, may hinder chatbot adoption in purchasing decisions within the valence framework. Contributions to existing literature: (1) The study provides new insights into purchasing decisions facilitated by chatbots within the valence framework. (2) It introduces Openness to Change and Compatibility as new elements in analyzing chatbot usage.(3) It presents a novel investigation into chatbot utilization within the valence framework, specifically incorporating Openness to Change and Compatibility. The findings underscore the significance of Openness to Change in chatbot usage within the valence framework, suggesting that leveraging chatbots for purchasing decisions requires accounting for this factor to optimize benefits and mitigate risks.

Limitations and Future Research: (1) The study's sample was homogeneous, predominantly from Sumbawa Regency, potentially limiting generalizability.(2) Future research could enhance applicability by: a. Broadening the sample size b. Incorporating participants from diverse regions or countries.(3) The study focused primarily on consumer purchasing decisions, but future research could: a. Investigate other aspects of consumer behavior b. Categorize issues according to various facets of consumer behavior across different industries c. Explore the roles of each variable in contexts with distinct levels of benefits and risks In conclusion, this research provides valuable insights into chatbot usage in purchasing decisions, highlighting the importance of Openness to Change within the valence framework. However, it also acknowledges the need for broader, more diverse studies to enhance the generalizability and applicability of these findings across different contexts and consumer behaviors.

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