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An In-depth Investigation into the Influence of Chatbot Usability and Age on Continuous Intention to Use: A Comprehensive Study

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ABSTRACT

This study aims to assess the impact of chatbot usability and demographics on continuous intention to use across different sectors. The research employed Braun's Bot Usability Scale (BUS11) to measure chatbot usability, focusing on accessibility, quality, conversation quality, privacy risk, and response time. A total of 187 participants completed a survey as part of this study. Variance-based SEM was utilized to examine relationships and test hypotheses. This study contributes to the ongoing discourse on chatbot adoption and user behaviour. It enhances the understanding of chatbot usability, highlighting the role of age in continued intention to use chatbots. The findings suggest that different age groups may possess specific preferences and expectations regarding chatbot usability. These differing preferences can influence their intention to continue using this technology. The study reveals that chatbot usability significantly impacts continuous intention to use and that age moderates the relationship between perceived conversation quality, information, privacy, security, and continuous intention to use. Based on the study's results, it is recommended that chatbot designers enhance usability to promote long-term adoption and usage.

Keywords: Chatbot, Usability, Continuous Intention to Use, Demographics, Technology Acceptance

Ⅰ. Introduction

In the rapidly evolving digital landscape, chatbots have become indispensable for companies across various sectors such as Banking and Finance, E-commerce, and more. Powered by Artificial Intelligence (AI), these conversational agents have revolutionized customer care by providing immediate assistance and guidance to users. Chatbots' role for businesses have evolved from being just a consumer interaction tool to one that can help maintain competitiveness (Belanche et al., 2019; Davenport et al., 2020; Sousa

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and Rocha, 2019). With the integration of chatbots into the online consumer experience in recent years (Luo et al., 2019), customers often fail to distinguish between interactions with chatbots and humans. The utilization of chatbots by companies to engage with customers has been made possible through AI (Hollebeek et al., 2021; Sidaoui et al., 2020). Furthermore, businesses leverage technology to provide customer support services that cater to the evolving needs of their customers (Huang and Rust, 2021). By offering reliable advice, chatbots can create the perception of personalized communication tailored to individual needs. This emphasizes how important it is for a business to maintain its credibility by meeting customer expectations without creating new difficulties (Prentice et al., 2019). For marketing managers aiming to enhance customer satisfaction, understanding the factors influencing consumers' continued intention to use chatbots is crucial. This research seeks to explore the relationship between chatbot usability and ongoing intention to use, with age acting as a moderating factor.

Despite the availability of several studies on chatbots (Borsci et al., 2022; Holmes et al., 2019; Larbi et al., 2022), there is limited research on chatbot usability and continuous usage intention. Previous studies have mainly concentrated on the initial adoption of chatbots, overlooking the examination of users' ongoing usage. To evaluate user satisfaction with chatbots, Borsci et al., 2021 have developed tools such as the BOT-Check checklist and the BOT Usability Scale (BUS-15), which consider various dimensions including conversational efficiency, accessibility, and functionality.

Furthermore, although chatbot usability has been extensively studied, few research studies have explored the relationship between usability and continued usage. While assessing the user experience of a COVID-19 chatbot, users reported high scores for usefulness, ease of use, and satisfaction, while also identifying areas for improvement in terms of usability and health support (Chagas et al., 2022). However, there is a need for more formal experiments to measure user experience and provide design guidelines in the emerging field of chatbot usability (Ren et al., 2019). Therefore, there is a need for research that investigates chatbot usability and its connection to continuous intention to use chatbots (CIUC) (Li et al., 2021). Additionally, as chatbot usage expands and different age groups interact with it, it becomes crucial to study consumers across various age groups and consider their preferences and expectations (Wu et al., 2021). The research questions addressed in this study are as follows:

1. How does perceived accessibility impact the CIUC among users?

2. What is the relationship between quality and the CIUC among users?

3. How does conversation and information quality influence CIUC among users?

4. What is the relationship between privacy and CIUC among users?

5. How does timely response affect CIUC among users?

6. Which usability aspects have significant effects on CIUC among different age groups?

Ⅱ. Literature Review and Hypothesis

Hendriks et al. (2020) conducted a study on the impact of chatbot self-presentation on user experience, specifically focusing on social presence, perceived humanness, and service encounter satisfaction. Their findings revealed that a chatbot disclosing its virtual identity scored significantly lower for social presence and perceived humanness compared to other methods of self-presentation. This insight is crucial for chatbot designers and contributes to relevant theories on chatbot interaction. (Lesselroth et al., 2020) conducted a comprehensive review of user experience (UX) theories, models, and frameworks in the context of healthcare. Their aim was to identify and summarize relevant theoretical models and frameworks used to study health information technology (HIT) and user experience in healthcare, emphasizing the significance of understanding user experience in the context of healthcare technology. (Antle and Wise, 2013) aimed to provide a comprehensive framework for understanding the relationships between tangible user interface features, interactions, and learning, emphasizing the importance of tangible user interface design in impacting learning outcomes. (Fu, 2012; Gomez et al., 2012) studied user interface design by applying aesthetic theories, incorporating Gestalt principles, color theory, and typography theory to create visually appealing and usable interfaces. Their work underscored the significance of integrating aesthetic and usability principles to enhance overall user experience. (Oh et al., 2022) suggested a comprehensive study delving into the user experience and usability aspects of digital museum interfaces, emphasizing the importance of designing interfaces that meet user goals, integrate various information types, and utilize intelligent sensing technologies to enhance usability. (Kim et al., 2019) proposed an analysis of skeuomorphism in iOS interfaces, aiming to interpret this design approach through Simulacrum Continuous Phase Theory, highlighting the psychological and experiential implications of skeuomorphic design in iOS user interfaces.

In addition to the existing literature, the study of user experience and usability theories is crucial for understanding chatbot usability. By delving into these theories, researchers and designers can gain insights into how chatbot interactions can be optimized to enhance user satisfaction, trust, and engagement. Understanding user experience and usability theories in the context of chatbots can lead to the development of more effective and user-friendly chatbot interfaces, ultimately improving user interactions and overall satisfaction. Moreover, as chatbot technology continues to evolve, studying user experience and usability theories can help designers and researchers adapt to new trends and technologies, ensuring that chatbot interfaces remain relevant and effective in meeting user needs and expectations.

Ⅲ. Chatbot Usability

Usability and responsiveness are two crucial aspects of a chatbot. Usability, as defined by (Petre et al., 2011), refers to the ease with which users can effectively, efficiently, and satisfactorily complete specific tasks using a human-computer interface. Previous research has examined user engagement with chatbots, highlighting the importance of perceived usefulness, ease of use, and societal impact in early acceptance (Følstad and Brandtzaeg, 2017). However, these studies have not explored CIUC. User interaction metrics for usability, as highlighted by Finstad (2010), shed light on the factors influencing usability. Organizations that employ chatbots for initiating conversations or explaining product/service operations in e-commerce are perceived as innovative rather than untrustworthy (Joyce and Kirakowski, 2015).

Verhagen et al., 2014studied continuance intention and found that perceived usefulness and prior use were significant indicators of CIUC. However, this study was limited to specific industries such as Banking and Finance and e-commerce, and did not consider other potential influencing factors. Trust has also been identified as a factor influencing the continuous desire to use chatbots (Gnewuch et al., 2017), but a comprehensive analysis of the factors influencing trust is needed. Perceived accessibility, quality, conversation and information quality, privacy, and timely response are critical factors that can impact the overall user experience with chatbot. (Gnewuch et al., 2017).

3.1. Accessibility

Perceived accessibility refers to the subjective measure of how well individuals with specific disabilities, skills, and goals experience the accessibility of applications or services. It is influenced by factors such as the complexity of user interface elements, individual characteristics, and the availability of opportunities in the surrounding environment. Studies have shown that perceived accessibility may not always align with spatial accessibility calculated from spatial data (Islam et al., 2023). Individual factors, such as car mobility and social disadvantages, can moderate the perception of accessibility (Pot et al., 2023a). Residential self-selection also plays a role in perceived accessibility, as people may choose to live in areas that match their preferences for out-of-home activities (Pot et al., 2023b). Perceived accessibility refers to the ease with which users can access and utilize the chatbot. A well-designed chatbot should have simple prompts and replies that guide users through the conversation, as well as the ability to understand user inputs in various formats, including natural language requests (Chung et al., 2020). The significance of flexible, accurate, and comprehensive interactions in fostering positive perceptions of comprehension and relevant communication has also been emphasized (Chung et al., 2020). Providing explicit, clear, and easy-to-read information and maintaining a coherent dialogue can make customers feel valued and comfortable (Go and Sundar, 2019). Based on these considerations, we propose the following research objectives.

H1: Perceived accessibility positively influences continuous intention to use.

3.2. Quality

Chatbot's response quality and information accuracy are extremely important to users. Users expect chatbots to deliver prompt and reliable information that is relevant to their needs. According to research conducted by (Gray et al., 2007), while chatbots may not possess the same level of emotional intelligence as humans, a chatbot that consistently delivers superior responses can help build confidence and trust in technology. The perceived quality of a chatbot's performance has a positive and significant impact on users' intention to repurchase or continue using a service in various contexts. For example, a study conducted by Tarmidi et al. (2022) found that perceived value and perceived quality positively influence users' intention to repurchase the Spotify app. Similarly, Suryawirawan et al. (2022) discovered that reliability and responsiveness, which are dimensions of service quality, have a positive impact on customer satisfaction and the intention to continue using a service. Furthermore, a study by (Azzahra and Kusumawati, 2023), focusing on MyTelkomsel app users, revealed that the quality of service content and customer service positively affect perceived value and customer satisfaction, which, in turn, influence users' intention to continue using the app. These findings highlight the crucial role of perceived quality in shaping users' intention to continue using chatbot services. Based on this, we propose the following.

H2: Perceived quality positively influences continuous intention to use.

3.3. Conversation and Information

The perceived quality of conversation and information provided by a chatbot depends on its ability to engage users in meaningful discussions and offer accurate and relevant information. A high-quality chatbot is capable of understanding user queries and responding appropriately. Users are more likely to prefer a chatbot that consistently delivers accurate and relevant information, leading to increased engagement and satisfaction. Moreover, the quality of a chatbot's responses plays a crucial role in enhancing customer service chatbot systems and creating enjoyable conversations (Li et al., 2021).

In addition, a study conducted by (Akdoğan and Kuru, 2022) found that the perceived quality of information in a virtual travel experience and the satisfaction derived from the sense of that virtual travel experience positively and significantly influence the intention to visit the corresponding destination in the real world. Furthermore, (Maria et al., 2021) discovered that the quality of information and service has a positive impact on the perceived value, which, in turn, influences the intention to engage with the customer. Lastly, Muslichah, 2018 found that the perceived quality of information directly and significantly affects the intention to use an academic information system. Based on these findings, we propose the following.

H3: Perceived quality of conversation and information positively influences continuous intention to use.

3.4. Risk

When using chatbots, consumers may have concerns about the privacy and security of their data. It is important for chatbots to follow data protection standards and be transparent about the information they collect and how it is used. Users are more likely to trust chatbots that prioritize user privacy and provide options to opt out of data collection, leading to increased satisfaction and engagement (Chung et al., 2020; Zarouali et al., 2018). Additionally, users benefit from interacting with chatbots that require minimal effort (Prentice et al., 2019; Roy et al., 2018). The privacy risks associated with chatbots have an impact on users' intention to continue using them (Yang et al., 2023). Users' perception of privacy concerns can influence their decision to use chatbots (Ng et al., 2020). Privacy risks, such as data breaches and user profiling, are identified as potential threats to chatbot security (Waheed et al., 2022). However, the presence of socio-emotional features in chatbots does not necessarily increase users' trust levels or reduce their privacy concerns (de Cosmo et al., 2021). Based on these considerations, we propose the following.

H4: Privacy risk positively influences continuous intention to use.

3.5. Timely Response

The ability of a chatbot to provide quick and efficient solutions to user queries, known as immediate response, is highly valued by users. A chatbot that effectively addresses user inquiries and offers prompt responses is perceived as high-quality, leading to increased engagement and satisfaction. Users appreciate the convenience of being able to interact with chatbots outside of regular business hours, as they provide 24/7 customer care (Adamopoulou and Moussiades, 2020). However, there are differing opinions on the impact of instant versus delayed responses on the perception of chatbot human-likeness (De Cicco et al., 2020).

Additionally, the response time of chatbots can influence the social presence and usage intentions of both novice and experienced users (Chen et al., 2020). Based on these findings, we propose the following.

H5: Timely response positively influences continuous intention to use.

3.6. Moderator

Age has been identified as a significant factor influencing the adoption and utilization of chatbots, with younger individuals displaying higher levels of technology adoption and a greater likelihood of accepting and using chatbots compared to older individuals (Terblanche and Kidd, 2022). Various studies have found that age moderates the usability and intention to use chatbots in different contexts. For instance, in a study by (Terblanche, 2020), age was found to moderately influence effort expectancy in the adoption of coaching chatbots. Similarly, (Chung et al., 2021) examined the feasibility, usability, and effectiveness of a physical activity chatbot and reported that the average age of participants was 49.1 years, highlighting the relevance of age in chatbot usability. Additionally, (To et al., 2021) conducted a study during the COVID-19 pandemic and discovered that young adults and health workers assessed the usability and credibility of a web-based chatbot, emphasizing the importance of age in determining chatbot usability and intention to use. These findings suggest that younger age groups exhibit increased technological familiarity, higher levels of digital literacy, and more positive attitudes toward technology, which contribute to their greater acceptance and continued use of chatbots.

H1a: Age moderates the effect of Chatbot usability on Continuous Intention to Use.

Ⅳ. Research Method

An online structured survey was designed and distributed to gather data for this research. To assess chatbot usability, we utilized the Bot Usability Scale (BUS11) developed by (Braun, 2023a), which consists of 11 items. The BUS-11 was developed using the theories of user satisfaction and usability evaluation (Braun, 2023). To capture all the factors that affect users' happiness while engaging with chatbots, the original version of this scale included 42 items (Borsci et al., 2022). An attempt was made to shorten the list of things since it is lengthy and the ten-item System Usability Scale has already drawn criticism for being very lengthy. As a result, the five-factor BUS-15 was developed, with a reliability coefficient ranging from.76 to.87 (Borsci et al., 2021). Additionally, a strong relationship, suggests that it more accurately assesses the satisfaction construct. Since a 15-item scale is still lengthy, a shortened version is known as BUS-11. These 11 items also revealed the five-factor structure, although more validation research was advised (Borsci et al., 2021). This scale measures various aspects of chatbot usability, including perceived accessibility, perceived quality, perceived quality of conversation and information, perceived privacy and security, and timely response. These factors impact the likelihood of continued use from a user experience and satisfaction standpoint. If users see a service or product as accessible, high-quality, and providing valuable conversation and information, they're more likely to keep using it. Moreover, if users believe their privacy and security are safeguarded and they receive timely responses, they're more likely to stick with the service or product. Together, these factors shape overall user satisfaction and affect their intention to continue using the service or product in the long run. The BUS11 scale was adapted to align with the specific goals and context of our study, ensuring the relevance of each item to our research objectives. Continuous intention to use was measured using three items adapted from the work of (Al-Emran et al., 2020). Each item was evaluated on a five-point Likert-type scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The survey was administered online via Google Forms, with the study participants consisting of individuals aged 18 years and above. By incorporating participants from diverse age groups, we intend to utilize age as a moderator to investigate how different generational cohorts perceive and engage with chatbots. Different age groups may exhibit varying levels of technological proficiency and familiarity with chatbot interactions. By using age as a moderator, we can explore how these differences influence the ease of use and acceptance of chatbot interfaces among participants. the age groups "18 – 22 years," "23 – 27 years," "28 – 32 years," "33 – 37 years," and "38 years above" as numerical categories 1, 2, 3, 4, and 5, respectively, enabling statistical analysis and comparison across the age groups. To ensure the validity and reliability of the study, participants were required to respond to two screening questions regarding their awareness and usage of chatbots. Those who were not aware of or had not utilized any chatbots were excluded from the study. The chatbot-aware users were asked to provide their demographic information and details on their chatbot usage, experience, usability, and continuous intention to use.

A total of 192 responses were received, with 187 participants being aware of and having used chatbots, while five participants were not aware of chatbots. To determine the appropriate sample size, the guidelines proposed by (Hair et al., 2016) were followed. The minimum sample size should be greater than the larger of two values: ten times the maximum number of formative indicators used to measure a single construct or ten times the maximum number of structural paths directed at a specific latent construct in the structural model. In our study, the highest value among these figures was 14, indicating that a minimum sample size of 140 (14 times 10) would be required. However, our study exceeded this minimum requirement by collecting a sample size of 187.

Frequency analysis on SPSS for demographic profiles and Smart PLS 4 were employed to test the relationships and hypotheses in the study. Smart PLS 4 was chosen as the analytical tool due to its ability to handle formative models effectively. Unlike reflective models, formative models are characterized by indicators that directly cause the construct, and Smart PLS 4 is specifically designed to accommodate such models. This software allows for the estimation of complex relationships between observed and latent variables, making it well-suited for analyzing the formative nature of the structural equation model's components. Additionally, Smart PLS 4 provides robust statistical techniques for assessing the validity and reliability of the model, ensuring the accuracy and integrity of the analysis. The hypotheses were rigorously tested, and the validity and reliability of the constructs were evaluated. Measures such as composite reliability, Cronbach's alpha, and the extracted average variance (AVE) were used to assess the reliability and validity of the measurement items. It is important to acknowledge that common method bias can potentially impact the covariation among latent variables and influence the reliability and validity of the items. To address this concern, Harman's single- factor test, a widely used method (Podsakoff et al., 2003), was employed to examine the variation attributable to a single common method factor. Smart PLS includes a path model that allows for the specification of relationships between variables and indicators. This feature provides advantages in terms of relationship specifications and model complexity. Moreover, Smart PLS is not reliant on distributional assumptions, making it more adaptable to different data requirements (Hair et al., 2011).

Ⅴ. Results and Findings

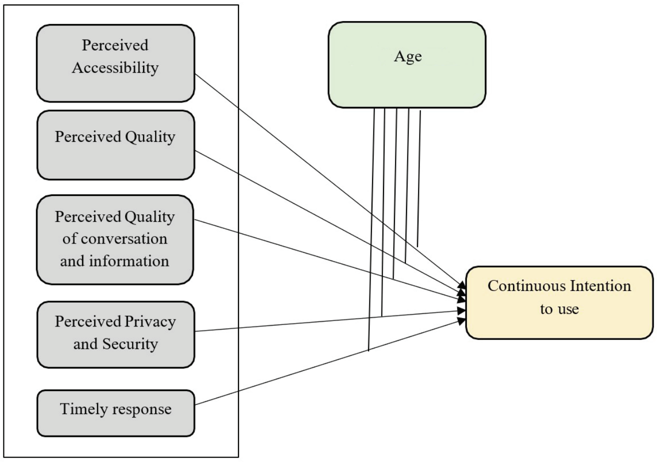
<Table 1> presents the demographic profile of the respondents. The sample consisted of a higher proportion of male participants (69%) compared to female participants (31%). In terms of age, the majority of respondents were 23 years old. Respondents between the ages of 23 and 27 accounted for 42% of the sample, while those between the ages of 28 and 32 accounted for 26%. In relation to the place of residence, the majority of respondents were from the City (54.5%), followed by Town (29.9%) and Village (15.5%). Additionally, a significant number of respondents (44.9%) reported having more than 1 year of experience with chatbots, and the majority of respondents (75.4%) held a Master's degree.

<Table 1> Demographic Profile

Age	Frequency	Percentage
18 – 22	20	10.7
23 – 27	79	42.2
28 – 32	49	26.2
33 – 37	29	15.5
38 above	10	5.3
Gender		
Male	129	69
Female	58	31
Education Qualification		
UG	38	20.3
PG	141	75.4
Others	8	4.3
Place of Living		
City	102	54.5
Town	56	29.9
Village	29	15.5
Experience using Chatbot		
Less than 6 months	47	25.1
7 months – 1 year	56	29.9
1 year above	84	44.9

Among the respondents, 32 reported using chatbots in the E-commerce industry, making it the most frequently utilized sector. This was followed by the Banking and Finance industry, with 26 participants. The Healthcare and Insurance sectors had the fewest participants, with only 5 and 8 respondents, respectively. Based on the ratings provided, the E-commerce, Food Delivery, and Travel and tourism industries were the most commonly utilized sectors for chatbots, while the Healthcare and Insurance sectors were the least utilized. It is worth noting that responses regarding the usage of chatbots in the Online Grocery sector were divided.

<Table 2> presents the results of a factor analysis conducted on variables assessing different aspects



<Figure 1> Conceptual Framework Chatbot Usability

of perceived service quality and accessibility. The factor loading column indicates the strength of the relationship between each item and its corresponding factor. Internal consistency reliability measures, including Cronbach's alpha, composite reliability, and average variance extracted (AVE), were calculated for each factor.

The findings indicate that the variables can be categorized into four distinct constructs: perceived accessibility, perceived quality, perceived quality of discussion and information, and continuous intention to use. The factor loading values demonstrate that the variables within each construct have significant relationships with their respective factors, indicating that they are reliable and valid measures of each construct. Additionally, high Cronbach's alpha, composite reliability, and AVE scores further support the reliability and validity of the measure-

<Table 2> Common Method Bias

Item	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Perceived Accessibility		0.592	0.830	0.709
PA1	0.869			
PA2	0.814			
Perceived Quality		0.746	0.853	0.660
PQ1	0.763			
PQ2	0.827			
PQ3	0.846			
Perceived Quality of Conversation and information		0.805	0.872	0.630
PQCI1	0.761			
PQCI2	0.842			
PQCI3	0.776			
PQCI4	0.795			

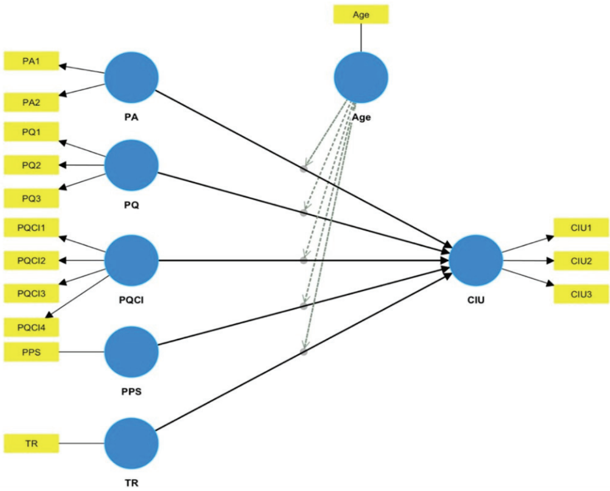
<Table 2> Common Method Bias (Cont.)

Item	Factor Loading	Cronbach's Alpha	Composite Reliability	AVE
Perceived Privacy and security		1	1	1
PPS1	1.000			
Timely Response		1	1	1
TR1	1.000			
Continuous intention to use		0.778	0.872	0.694
CIU1	0.806			
CIU2	0.816			
CIU3	0.875			

Note: (1) AVE is Average Variance Extracted. (2) All factor loadings were significant at the 0.05 confidence level

ment items within each construct.

The Fornell-Larcker criteria were employed to assess the reliability and validity of the measurement model. As shown in <Table 3>, the criteria were used to examine the relationships between various constructs, including age, continuous intention to use (CIU), perceived accessibility (PA), perceived quality (PQ), perceived quality of conversation and information (PQCI), perceived privacy and security (PPS), and timely responses (TR). The diagonal of the table displays the reliability of each construct, measured by Cronbach's alpha values. The values above the diagonal represent the correlation coefficients between each pair of constructs, while the values below the diagonal represent the extracted average variance (AVE) for each construct. The findings indicate that all constructs demonstrate reliability, as evidenced by Cronbach's alpha values exceeding 0.6. The AVE values indicate that each construct explains a significant percentage of the variation in its components. Furthermore, the correlation coefficients reveal varying degrees of association be-



<Figure 2> Path Model

<Table 3> Fornell-Larcker Criterion

	Age	CIU	PA	PQ	PQCI	PPS	TR
Age	**1.000**						
CIU	-0.242	**0.833**					
PA	-0.185	0.653	**0.842**				
PQ	-0.310	0.737	0.657	**0.813**			
PQCI	-0.159	0.724	0.624	0.736	**0.794**		
PPS	-0.198	0.643	0.488	0.587	0.616	**1.000**	
TR	-0.161	0.610	0.465	0.678	0.660	0.404	**1.000**

tween constructs. For example, PQCI exhibits the highest correlation with PQ (0.736) and the second-highest correlation with CIU (0.724). Similarly, PPS shows the highest correlation with CIU (0.643), following PQ (0.657) and PQCI (0.624). Conversely, age does not exhibit significant correlations with the other constructs.

Overall, the Fornell-Larcker criteria suggest that the measurement model demonstrates reliability, validity, and discriminant validity, as the constructs are distinct and not substantially associated with each other.

PA - Perceived Accessibility; PQ – Perceived Quality; PQCI – The perceived quality of conversation and information; PPS – Perceived Privacy and Security; TR – Timely Response; CIU – Continuous Intention to use.

The results of the study indicate a significant positive effect of perceived accessibility on continuous intention to use (β = 0.050, t = 1.964). Additionally, perceived usability of the chatbot has a significant positive impact on continuous intention to use at a 99% confidence level (β = 0.000, t = 3.728). Perceived privacy and security also show a positive and significant relationship with continuous intention to use at a 99% confidence level (β = 0.000, t = 3.554). Furthermore, timely responses are positively significant with continuous intention to use (β = 0.004, t = 2.899). These findings are presented in <Table 5>.

Moreover, the study reveals that age moderates the relationship between perceived accessibility and continuous intention to use, with a 95% confidence level (β = 0.045, t = 2.002). Similarly, age moderates the relationship between perceived quality of conversation and information and continuous intention to use, with a 99% confidence level (β = 0.000, t = 3.815). Additionally, age moderates the relationship between perceived privacy and security and continuous intention to use, with a 99% confidence level (β = 0.000, t = 5.119). These results support hypotheses H1a, H3a, and H4a.

While hypotheses H2 and H5a were not supported, hypotheses H1, H1a, H2, H3, H3a, H4, H4a, and H5 were supported by the findings. The direct effects of these hypotheses are presented in <Table 4>, which displays the outcomes of the partial least squares estimation. To assess the model's predictive potential, the explained variance (R^2) was used, revealing a significant variation in continuous intention to use (R^2 = 0.749). The normality of the data and the significance of the structural routes were estimated using bootstrapping with 1,000 samples and the PLS algorithm.

The moderating effects of age on the relationship between chatbot usability and continuous intention

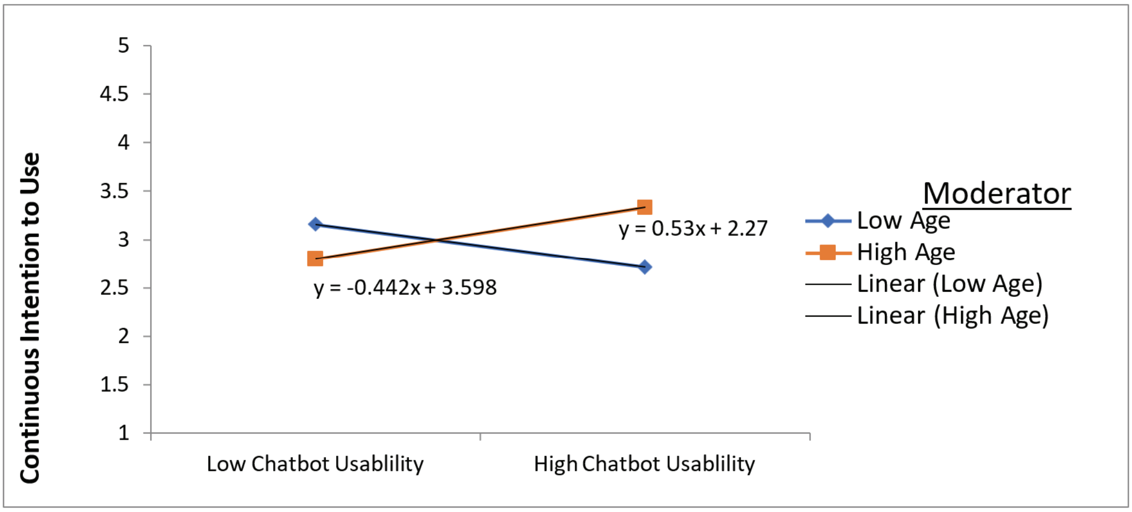
<Table 4> Path Co-efficient

	T-statistics	P Values	Results
Age → CIU	1.856	0.064*	Supported
PA → CIU	1.964	0.05*	Supported
PQ → CIU	3.728	0***	Supported
PQCI → CIU	1.917	0.055*	Supported
PPS → CIU	3.554	0***	Supported
TR → CIU	2.899	0.004***	Supported
Age × PA → CIU	2.002	0.045*	Supported
Age × PQ → CIU	1.03	0.303	Not supported
Age × PQCI → CIU	3.815	0***	Supported
Age × PPS → CIU	5.119	0***	Supported
Age × TR → CIU	0.165	0.869	Not supported

to use are depicted in <Figure 3>, illustrating a two-way unstandardised moderation graph.

VI. Discussion and Conclusion

The study examined the impact of various elements on chatbot usability and the intention to continue using chatbots. These attributes included perceived accessibility, perceived quality, perceived quality of conversation and information, perceived privacy, and timely response. The findings revealed that all these factors significantly influenced users' intention to continue using chatbots. In the context of electric vehicle (EV) adoption in Hong Kong, objective accessibility, perceived accessibility, and prospective accessibility of public EV charging facilities were found to significantly affect EV adoption intention (He et



<Figure 3> 2-way Interaction Effect

al., 2022). Perceived accessibility was particularly important for the age group of 23 to 27 years old, as they were more likely to continue using chatbots if they found them easy to use. Young adults in the 23 to 27 age range are typically more technologically adept and familiar with digital interfaces. Research shows that younger adults use a greater breadth of technologies compared to older adults (Colledge, 2018). However, age-related differences in technology usage and frequency of use depend on the specific technology domain (Michael et al., (2013). They have grown up in an era where technology is prevalent and have developed higher expectations for user-friendly experiences. As a result, they place a greater emphasis on chatbots that are easily accessible and provide a seamless user experience. When chatbots are perceived as accessible, it enhances the overall user experience and reduces any potential barriers to engagement. It allows individuals in this age group to quickly and effortlessly interact with the chatbot, which in turn leads to higher satisfaction and a greater intention to continue using it. On the other hand, perceived quality significantly predicted continued usage for users of all ages, with the perceived quality of conversation and information being especially crucial for the age group of 38 and above. The study also revealed that for individuals aged 38 and above, the perceived quality of conversation and information was particularly crucial in determining their continued usage of chatbots. This age group often places a higher emphasis on the quality of conversations and the accuracy of information provided by chatbots. However, they may have a greater need for additional human contact compared to younger adults (Han et al., 2022). Older adults also experience difficulty in assessing the security of chatbot communication (Iancu and Iancu, 2023). Individuals in this age group tend to have different preferences and expectations when it comes to technology. They may prioritize meaningful conversations and reliable information, as they value accuracy and relevance in their interactions. Therefore, chatbots that can engage in natural and coherent conversations while delivering accurate and helpful information are more likely to retain the interest and trust of users aged 38 and above. They were more inclined to continue using chatbots if they perceived the conversation and information quality to be high.

Perceived privacy was important for all users, regardless of age, Users who perceived the chatbot as privacy-conscious, meaning that it prioritized the protection of their personal information and adhered to privacy regulations, were more likely to continue using it. This finding suggests that users value their privacy and are more inclined to trust and engage with chatbots that demonstrate a commitment to safeguarding their personal data (Ait-Mlouk et al., 2023; Sebastian, 2023). Additionally, a timely response was important for all users. Users expect chatbots to provide prompt responses to their queries or requests. Chatbots that can deliver timely and efficient responses, minimizing waiting times, are more likely to satisfy users' needs and encourage them to continue using the chatbot (Gupta et al., 2023; Rajesh et al., 2023). This finding highlights the importance of providing a responsive and efficient user experience to retain users' interest and engagement.

The study also found that age influenced the relationship between perceived accessibility and intention to use. Perceived accessibility had a stronger impact on the age group of 23 to 27 years old compared to the age group of 38 and above. This suggests that chatbot creators should pay special attention to accessibility when targeting younger users. The research highlights the importance of creating approachable, high-quality, privacy-conscious, responsive, and engaging chatbots requires addressing several challenges. It is important to release an initial system of sufficient quality to encourage human interaction (Ackerman et al., 2022). These findings align with the existing literature on chatbot usability and user perceptions. The results of this study are in line with previous research, highlighting the need for successful and interesting chatbot designs across a variety of businesses (Jenneboer et al., 2022).

Ⅶ. Theoretical Implications

The research contributes to the current understanding of chatbot adoption and user behaviour by evaluating the relationship between chatbot usability and users' continuous intention to use them across various sectors. The study contributes to the understanding of user experience by examining the influence of chatbot usability factors on users' continuous intention to use. It provides insights into how perceived accessibility, quality, conversation and information quality, privacy, and timely response impact users' overall experience with chatbots. A wide range of research on user experience, interface design, and chatbot interaction. Insights from studies on healthcare user experience, tangible user interface design, aesthetic theories, digital museum interfaces, and skeuomorphism in iOS interfaces form a strong foundation for the theoretical implications of the proposed comprehensive study. These implications include the importance of understanding how chatbot usability and demographic factors intersect within specific domains, such as healthcare, and how they affect continuous intention to use. Additionally, the study should delve into how tangible interface features in chatbots impact user behaviour and intention to use, especially across different demographic groups. It's also crucial to understand how aesthetic and usability principles in chatbot interfaces influence continuous intention to use across diverse demographic groups. Moreover, the study should investigate how chatbot interfaces can be designed to meet various user goals and information needs, and how these design aspects influence continuous intention to use. Lastly, the study should aim to interpret design approaches in chatbot interfaces and their impact on user experience and continuous intention to use, particularly across different demographic groups. By integrating these insights, the comprehensive study can provide valuable guidance for chatbot designers and researchers looking to enhance user engagement, satisfaction, and continuous intention to use across diverse demographic groups. Ultimately, this can contribute to the advancement of chatbot technology and our understanding of user experience.

Ⅷ. Managerial Implication:

Various factors such as perceived accessibility, quality of dialogue and content, privacy, and rapid response, affect consumers' continued desire to use chatbots. Businesses and developers should prioritize these considerations when developing and deploying chatbots to improve the user experience and promote ongoing usage. The moderating impact of age on chatbot usability should also be taken into account, as different age groups may have varied feelings and expectations. Age-segmenting the target population and adjusting chatbot functionality accordingly can help meet the diverse demands of users.

The findings from the research across various industries can also assist firms in identifying sector-specific factors that may influence the adoption and usage of chatbots. Regular analysis of chatbot performance and user input is essential for identifying areas for improvement. By continuously developing chatbot features and functionalities based on user feedback, businesses can ensure that their chatbots remain relevant and engaging, resulting in higher usage frequency and user satisfaction. The study also highlights the importance of perceived privacy in determining consumers' willingness to continue using chatbots. When creating chatbots, businesses should prioritize data protection and implement security safeguards to instill customer trust in providing information and interacting with the chatbot.

Ⅸ. Limitations and Future Directions

The reliance on self-reported data in this research introduces potential biases, such as social desirability and recollection bias. While the study focuses on age as a moderator, it is important to acknowledge that other characteristics may also influence the relationship between chatbot usability and continuous intention to use. Future studies should consider including additional potential confounding variables, such as gender, education, income, and anthropomorphism, to gain a more comprehensive understanding of the factors that impact chatbot adoption and utility.

To further evaluate the long-term impacts of chatbot usability on continuous intention to use, future research could employ longitudinal study designs. This would allow researchers to track changes in user behavior and preferences over time, providing valuable insights into the factors that contribute to long-term chatbot adoption. In this study, chatbot usability theory was utilized to assess chatbot usability and continuous intention to use. However, future studies should consider integrating established frameworks for technology acceptance, such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT). By doing so, researchers can gain a deeper understanding of the factors that influence consumers' continuous intention to use chatbots.

Furthermore, future research could focus on analyzing how various chatbot design factors and functions impact usability and continuous intention to use. This would provide valuable guidance for firms seeking to improve their chatbot solutions and for chatbot creators. By identifying the design elements that support enhanced usability and continued user engagement, developers can make informed decisions to produce more effective and user- friendly chatbot experiences.

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