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An Exploration of Millennials' Attitudes Towards the Use of Artificial Intelligence Chatbots for Customer Service within E-commerce Platforms.

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Abstract

The research aims to identify the determinants impacting millennials' adoption intention towards AI-powered chatbots in eCommerce customer service. This quantitative study employed a survey instrument to collect data from 113 millennials, utilizing a convenience sampling approach. The well-established Technology Acceptance Model (TAM) served as the foundation, extended to incorporate trust and social influence alongside perceived usefulness and ease of use. Linear regression analysis tested the hypothesized relationships. The findings reveal a significant positive influence of all four factors (PU, ease of use PU, PEOU, trust, and SI) on millennials' intention to utilize AI chatbots. Trust emerged as the most impactful determinant. The study's generalizability might be limited due to the sample size and recruitment method. Future research should consider a more diverse sample encompassing socio-cultural, technical, and socioeconomic factors. E-commerce companies can leverage these findings to optimize their AI chatbots for customer service and achieve greater adoption among millennials. Strategies include prioritizing trust-building mechanisms, harnessing social influence, enhancing the perceived usefulness of the chatbot's functionalities, and ensuring user-friendly interfaces. This research contributes to narrowing the knowledge gap by investigating factors influencing millennials' adoption of AI chatbots in eCommerce customer service.

Keywords: AI Chatbots, Customer Service, Electronic Commerce, Millennial, Technology Acceptance Model (TAM)

1. Introduction

The global landscape is undergoing a rapid transformation due to the increasing digitisation of various aspects of society. The increasing amount of online customers, along with the fast-evolving business landscape, necessitates that eCommerce differentiates itself by offering enhanced levels of service to customers and a better experience for clients (Vijayakumar Bharathi et al., 2022). The responsibilities of chatbots have experienced a metamorphosis due to these advancements, which organisations employ to maintain their competitive edge. In recent years, there has been a notable integration of chatbots into the online customer experience, resulting in a seamless interaction that often renders customers unable to discern between engaging with an AI chatbot or an actual human. This phenomenon is particularly applicable to the younger generation, sometimes referred to as millennials, who were born between the years 1981 and 1996. These individuals heavily rely on technology in their day-to-day activities, particularly within the professional setting (De Cicco et al., 2020). Millennials, being the initial cohort to have come of age during the era of the smartphone, exhibit a preference for personalised attention, while concurrently displaying a reduced tolerance for waiting. Chats have become the preferred manner of customer service for millennials due to their real-time nature, allowing for prompt and casual responses to concerns. Hence, chatbots are emerging as a solution to meet this need, with the goal of providing personalised and readily available services to cater to the preferences of the youthful customer base. This level of convenience and customisation is unattainable through traditional means (Nichifor et al., 2021). In spite of growing interest in AI chatbots, there is still a significant deficit in the form of quantitative studies (Sun et al., 2023). Such studies might provide firms with vital data and insights to proficiently utilise this technology in customer care. The purpose of this investigation is to explore further into the factors that make young people/customers feel at ease when interacting with artificial intelligence chatbots in the customer service sector.

In the last decade, real-time chat has become the go-to for e-commerce customer service, replacing traditional methods (Charlton, 2013). Customers use chat to get info or resolve issues, fostering a dynamic exchange that impacts trust, satisfaction, and loyalty (Mero, 2018). Today, chatbots – AI-powered conversational agents – are often used instead of live chat representatives. Millennials, comfortable with interactive tools, value the convenience and accessibility chatbots offer (Chung et al., 2020). E-commerce has seen a rise in AI chatbots, which improve customer service efficiency by addressing queries, offering suggestions, and streamlining operations (De Cicco et al., 2020). However, inappropriate chatbot responses can create a gap between user expectations and reality (Luger & Sellen, 2016).

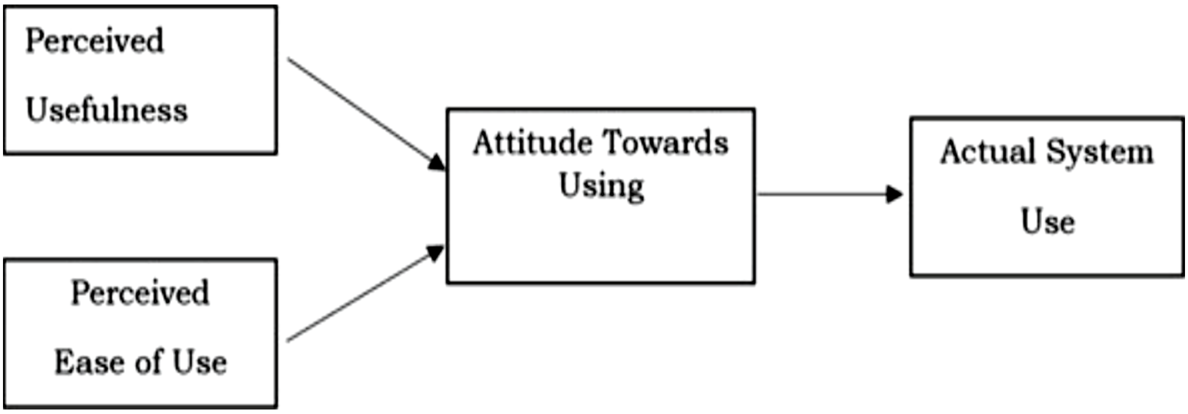
Millennials represent a significant population within the discipline of electronic commerce, rendering their perspectives crucial in comprehending the ramifications of artificial intelligence chatbots. This study addresses the lack of knowledge about millennials’ perceptions of AI chatbots’ functionalities and effectiveness. The research examines factors influencing millennials' adoption of AI chatbots for customer service. It aims to advance the understanding of AI chatbot adoption by applying the established Technology Acceptance Model (TAM) proposed by Davis (1986). Specifically, we have tried to answer how perceived usefulness (PU), perceived ease of use (PEOU), social influence, and trust impact millennials’ readiness and intent to use AI chatbots. The population group under consideration in this research includes individuals belonging to the millennial generation, which refers to the individuals who were born between 1981 and 1996 (Dimock, 2019), and who are the market's biggest and most technologically savvy customers (Lantos, 2014). Therefore, A quantitative approach was chosen, using a survey to collect data from millennials who have used e-commerce chatbots for customer service. The study intends to contribute academically to the literature on chatbot implementation in eCommerce, offering insights and recommendations. Chatbots mitigate eCommerce challenges, enhance efficiency by supplementing frontline staff, and improve customer service interactions. Understanding the psychological and emotional impacts of chatbot interactions is crucial for enhancing customer experiences and guiding practical applications in eCommerce settings.

2. Literature Review

Modern organisations encounter a constantly changing and developing environment (Setiawati et al., 2022), driven by ongoing advancements in information and communication technology, which creates numerous opportunities for the digital transformation of various business operations and entire businesses (Stojanov, 2019). Furthermore, the progress of technology is transforming various parts of society and simplifying everyday activities. Businesses are progressively integrating digital touchpoints into the purchasing process in order to improve consumer relations (Hagberg et al., 2016). In response to the shift to online shopping, businesses are enhancing the online customer experience by implementing customized recommendation systems, virtual shopping assistants, and electronic service agents. AI-driven chatbots are transforming service interfaces from human-centric to technology-centric, gaining significance for firms with extensive service engagements (Castillo et al., 2021). The growing customer preference for digital platforms has elevated the importance of AI-powered e-service agents, or chatbots, in business. These virtual assistants are replacing human agents, fostering meaningful connections, and providing seamless customer support (Selamat & Windasari, 2021). With the fast progression of artificial intelligence (AI), the eCommerce industry has seen a notable trend in the adoption and implementation of chatbots; as chats are the preferred option for millennials to use customer support (De Cicco et al., 2020), so they are taking the lead in embracing such technology. With chatbots becoming common in customer service and eCommerce, understanding the psychological foundation of young customers' experiences is essential. Millennials, a significant share of online customers, expect smooth, personalized digital interactions. Chatbots, capable of live one-on-one conversations, product recommendations (Sidlauskiene et al., 2023), and managing transactions, to meet these expectations. A deep understanding of millennial preferences and thought processes is crucial for effectively utilizing chatbots in eCommerce. Insights into their perceptions, trust in automated recommendations, and willingness to use chatbots can help businesses develop effective strategies. This study aims to understand the factors influencing millennials' interactions with AI chatbots, aiding eCommerce enterprises in improving customer satisfaction, sales, and competitiveness.

The Technology Acceptance Model (TAM), proposed by Davis (1986), is widely regarded as the most accepted theory for studying user acceptance behaviour (Liu et al., 2009). Davis developed the TAM model to investigate users' propensity to adopt various technologies, including chatbots, and to forecast the factors that influence their decisions (Davis et al., 1989; Venkatesh, 2000). TAM combines key factors associated with user motive, such as the perceived ease of use (PEOU), perceived usefulness (PU), and attitudes towards technology, along with outcome factors, including behavioural intentions and actual technology utilisation (Figure 1) (Davis, 1986). PU and PEOU are considered to be crucial variables that explain the outcomes either directly or indirectly (Marangunić & Granić, 2015). According to Davis et al. (1992), the PU of a technology is defined by people's expectations of how it will enhance their job performance. The PEOU of a technology is determined by the extent to which individuals perceive it as effortless and convenient for performing their tasks. Additionally, TAM is a relatively straightforward concept that can be expanded in many ways; as a result, numerous extensions that incorporate other theories have surfaced in the literature (Zhang et al., 2008). Based on relevant literature, we aim to extend the simple TAM model by including constructs that illuminate millennial consumers' intentions to use chatbots for eCommerce customer service.

Figure 1. Technology acceptance model as proposed by Fred Davis (1986)



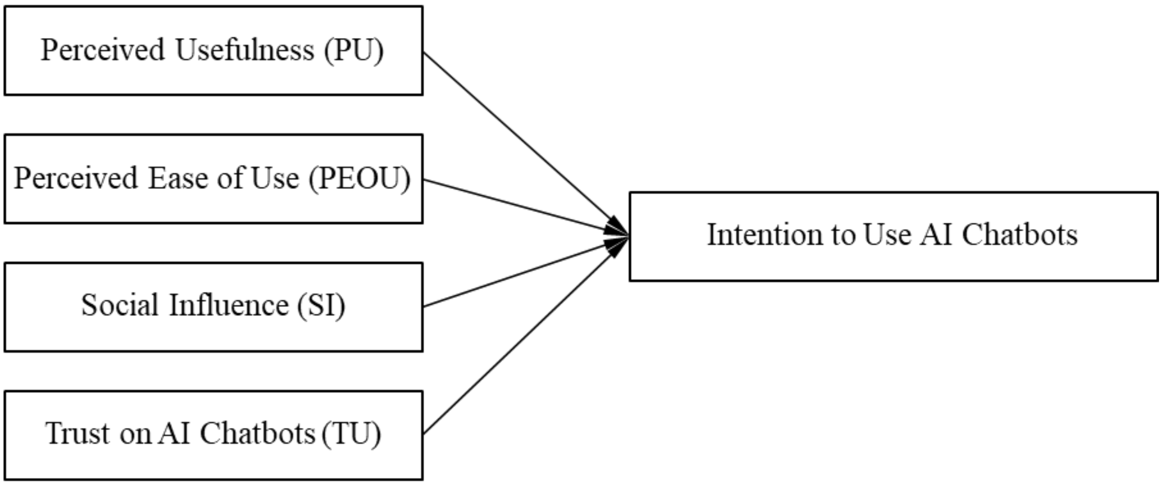
Source: Davis (1986)

In their study, Taylor & Todd (1995) conducted a comparative evaluation of the well-known theory of planned behaviour (TPB) (Ajzen, 1991) with the theory of reasoned action (TRA) (Fishbein & Ajzen, 1975). This study examined the impact of prior exposure to a certain type of technology on the connection between subjective norms Theory of Planned Behaviour (TPB) and TAM in terms of accepting technology. The results indicated a significant effect of subjective norms, which refer to social influence, on the intent to use technology, irrespective of previous experience. Significantly, this influence shown stronger consistency among the group that was unfamiliar with the technology. Consequently, as the knowledge of technology advances, people will be significantly more impacted by expectations from society. The study characterises this phenomenon as the outcome of an individual's societal obligation to employ technologies, as opposed to individuals with exceptional expertise.

Trust stands out as a significant determinant influencing the intention to utilise a chatbot, as stated by Gatzioufa & Saprikis (2022), among other variables. The study by Dahlberg et al. (2003) demonstrates that the technology acceptance model, which is trust-enhanced, accurately describes how users adopt new technologies. Trust has a direct and indirect impact on intention. Notably, the indirect effect operates through fostering a positive attitude towards new technology such as shopping in an eCommerce setting (Pavlou, 2003). Since chatbots are still new for many people, so trust plays a pivotal role in elucidating users' intentions and attitudes towards the use of chatbots (Kasilingam, 2020).

Recent studies have shown that attitudes regarding the use of technology do not completely mediate the connection between purpose and actual use (Kabir & Islam, 2021). Therefore, this study utilises a revised TAM paradigm that omits it. We hypothesise that actual usage is directly influenced by usage intention, which aligns with the fundamental principle of TAM paradigm that states intention is a direct indicator of actual usage (Davis, 1989). Considering this, we simplify the research framework by concentrating completely on assessing the intention to use and bypassing the actual usage (Figure 2).

Figure 2. Extended Technology Acceptance Model



Modified from source: (Kabir and Islam, 2021)

Quantifiable hypotheses are essential to address the research question. The TAM framework, encompassing PU and PEOU, forms the core framework. Additional variables like social influence and trust are derived from analogous technologies due to limited research on AI chatbots adoption.

2.1. Perceived Usefulness (PU)

Davis (1989) defines PU as the individual likelihood that employing a certain application system will improve the user's job or life performance. In contrast, Ajzen (1991); Rouibah et al. (2011) have explained PU as the degree to which potential customers believe that utilising information technology will result in substantial benefits for them. PU was defined by Davis et al. (1992) as "consumers' perceptions concerning the result of an experience." In addition, perceived usefulness refers to the extent to which a user believes that utilising a specific system would improve their job performance, hence positively influencing their intention to utilise the system (Ajzen, 1991; Chen et al., 2007). PU is a key predictor of the invention stage (Revels et al., 2010). According to Tan & Lim (2023), more and more inventive and creative technologies are emerging in the world in the modern day. Hence, these technologies must possess the attribute and quality of perceived usefulness in order to effectively assist technology users in enhancing their job and life efficiency. From a chatbot's perspective, its job is to assist consumers by providing them with accurate information that will fix their problems. Thus, the following hypothesis can be formulated.

H1: The intention to adopt AI Chatbots is positively influenced by Perceived Usefulness (PU).

2.2. Perceived Ease of Use (PEOU)

PEOU, as defined by Davis (1989), refers to the extent to which a potential user anticipates that the target system will need minimal effort. Alternatively, Venkatesh (2000) defined PEOU as "an individual's impression of the level of difficulty in learning and utilising the innovation." In addition, Morosan (2012) described PEOU as the circumstance in which people are inclined to adjust their behaviour towards a new technology if they consider it to be simple. A system is regarded useful, according to Davis et al. (1992), if it facilitates simplicity of use. An effective system has the capability to activate the inherent motivations of the users to engage with the system. Rahi et al. (2018) concluded that the ease of use is a crucial factor in predicting customer acceptance of technology. A user-friendly system possesses the capacity and prospect to entice consumers to utilise it (Tan & Lim, 2023). Therefore, it is imperative for the chatbot system to include user-friendly features, thereby fostering more adoption and interaction within the eCommerce domain. The preceding discussions served as the basis for developing the following hypothesis.

H2: The intention to adopt AI Chatbots is positively influenced by Perceived Ease of Use (PEOU).

2.3. Social Influence (SI)

Based on the definition of social influence (SI) given by Venkatesh et al. (2003) as the perceived pressure to implement a new technology by significant others, this study also claims that peer opinions significantly impact technology acceptance, as people, driven by a need for validation from respected peers, easily adhere to their technology preferences. During the period of the COVID-19 pandemic, there has been a notable surge in the implementation of AI-driven business applications, including chatbots (Gkinko & Elbanna, 2023). However, it is widely recognised that chatbots are susceptible to errors, which has an adverse effect on the dissemination of negative perceptions via word-of-mouth (Seeger & Heinzl, 2021). Nevertheless, the commercial demand for chatbots remains substantial, driven by its advantages, leading corporations to actively promote its adoption among their clientele (Xu et al., 2022). Davis (1986) did not show a direct link between SI and using technology, but Addis did show that subjective norms like SI have an instant effect on use intention. Venkatesh & Davis (2000), Venkatesh & Bala (2008) expanded upon the TAM paradigm by suggesting that social influence plays a role in shaping individuals' intention to adopt technology. The usefulness of the technology acts as a mediator for this influence. Gatzioufa & Saprikis, (2022) found that social influence has a significant impact on individuals' adoption and usage of chatbots. Researchers should prioritise considering this factor. Thus, the subsequent hypothesis is formulated.

H3: The intention to adopt AI Chatbots is positively influenced by Social Influence (SI).

2.4. Trust in AI Chatbots

Previous studies highlight the critical role of trust in technology adoption (Dhagarra et al., 2020; Shahzad et al., 2019; Silva et al., 2023). Trust is established when individuals feel their vulnerabilities won't be exploited in risky online interactions (Aljazzaf et al., 2010; Corritore et al., 2003), closely linked to privacy protection (Bhattacherjee, 2002). In e-commerce, trust significantly influences user behaviour (Gefen & Straub, 2003; Holsapple & Sasidharan, 2005). Trust is essential in both human-to-human and human-to-computer interactions (Agarwal, 2021). AI-powered chatbots, unlike non-AI technology, engage in natural language interaction, creating a sense of social presence and friendliness akin to human interaction (Koponen & Rytsy, 2020; Pizzi et al., 2021; Potdar et al., 2018). People are more likely to trust technology that fosters social presence (Ogonowski et al., 2014). Users often can't distinguish between chatbots and humans during interactions (Candello et al., 2017), perceiving chatbots as human-like (Nordheim et al., 2019). Anthropomorphizing chatbots enhances the emotional aspect of trust (De Visser et al., 2016; Mostafa & Kasamani, 2022; Pizzi et al., 2021). Building on Eren's (2016) emphasis on trust, this study proposes that trust significantly shapes user satisfaction with chatbot services (Eren, 2021). This leads to the formulation of the fourth hypothesis:

H4: The intention to adopt AI Chatbots is positively influenced by Trust.

3. Methodology

3.1. Research Philosophy and Design

This study adopts positivism, testing TAM theories deductively with quantitative surveys for hypothesis validation. It employs structured questionnaires for unbiased data collection and statistical analysis, with an exploratory component for deeper insight into millennial adoption of AI chatbots.

3.2. Population and Sampling

The research focused on the millennial demographic, which comprises individuals aged 26 to 42 as of December 31, 2023. We utilised the sampling approach called convenience sampling in this study. Convenience sampling is a non-probability sampling technique, which simply entails selecting study participants based on how convenient they are for the researcher (Bryman & Bell, 2015). According to Andrade (2020), determining sample size is crucial; too large or too small samples are considered unethical or irrational. G*Power software aids in computing sample size and power analysis (Kang, 2021). Using parameters of effect size 0.15, power 0.80, and significance level 0.05, G*Power (version 3.1.9.7) recommended a sample size of 85 (Table 1). Initially, 118 surveys were collected; after excluding five due to age criteria, 113 valid questionnaires remained for analysis.

3.3. Data source and collection

This study relies on primary data collection to obtain precise information. Primary data, as defined by (Hox & Boeije, 2004), is gathered specifically for the study's subject using appropriate methods, contributing new knowledge. It employed a cross-sectional survey design with self-administered close-ended questionnaires via Microsoft Forms in January 2023, spanning three weeks. Non-probabilistic convenience sampling methods were used to engage millennials familiar with chatbots via social media (LinkedIn, Facebook, WhatsApp), online platforms, email, and in-person meetings, though acknowledging potential selection bias.

*Table 1. Estimated sample size using G*Power*

F tests – Linear multiple regression: Fixed model, R^2 deviation from zero			
Analysis:	A priori: Compute required sample size		
Input:	Effect size f^2	=	0.15
	α err prob	=	0.05
	Power ($1-\beta$ err prob)	=	0.80
	Number of predictors	=	4
Output:	Noncentrality parameter λ	=	12.7500000
	Critical F	=	2.4858849
	Numerator df	=	4
	Denominator df	=	80
	Total sample size	=	85
	Actual power	=	0.8030923

3.4. Questionnaire development

A standardized questionnaire employing a 5-point Likert (1932) scale (1 = "Strongly Disagree" to 5 = "Strongly Agree") gathered data for this study. It utilized both existing and adapted instruments tailored to meet study requirements, guided by the theoretical framework for data collection and analysis (Bryman & Bell, 2015; Ghauri & Grønhaug, 2005)). The survey consisted of two parts: the first gathered demographic data, while the second focused on key variables including Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI), Trust (TRUST), and Overall Intention to Use/Adopt AI Chatbot-based customer service (OIUAC). Prior to full distribution, a pilot test refined the questionnaire based on feedback regarding coherence, structure, style, language, and respondent acceptance.

Table 2. Questionnaire sources and number of items

Constructs	Number of items	Sources
Perceived Usefulness (PU)	4	Adopted from (Davis, 1989; Pikkarainen et al., 2004)
Perceived Ease of Use (PEOU)	4	Adopted from (Davis, 1986; Pikkarainen et al., 2004; Nysveen et al., 2005)
Social Influence (SI)	4	Adopted from (Terblanche & Kidd, 2022; Venkatesh et al., 2003, 2012)
Trust	4	Adopted from (Bhattacherjee, 2002; Kasilingam, 2020; Pillai & Sivathanu, 2020)
Overall Intention to Use/Adopt AI Chatbot-based customer service (OIUAC)	4	Adopted from (Abushanab & Pearson, 2007; Bhattacherjee, 2002; Pillai & Sivathanu, 2020; Venkatesh et al., 2012)

3.5. Data analysis method

The inquiry utilised IBM SPSS version 29.0 for the purpose of doing data analysis. Furthermore, (Bryman & Bell, 2015) confirm that the programme is widely used by quantitative researchers because of its dependable output, which makes it an indispensable tool for organising survey data and testing hypotheses. After some preliminary data cleaning in Excel, the raw data obtained from Microsoft Forms was transferred into SPSS for thorough statistical processes. Venkatesh and Davis (2000) found that in numerous research studies of TAM, PU consistently emerged as a significant factor influencing usage intentions and the standardised regression coefficients for this relationship were usually about 0.6. The study applies a linear regression model for the purpose of analysing and testing the hypotheses.

$$OIUAC = \beta_0 + \beta_1 PU + \beta_2 PEOU + \beta_3 SI + \beta_4 TRUST$$

Here, PU = “Perceived usefulness”, PEOU = “Perceived ease of use”, SI = “Social influence”, and TRUST = “Trust” in AI Chatbot-based customer service, are four independent variables; OIUAC = “Overall intention to use/adopt AI Chatbot-based customer service” is the dependent variable; β_0 = Intention to adopt AI Chatbot-based customer service without independent variables; β_1 , β_2 , β_3 , β_4 are the regression coefficients, indicate the average marginal impact of a one-unit increase in each independent variable on the dependent variable (OIUAC), while keeping all other independent variables constant.

4. Results and Discussion

4.1. Reliability Analysis

Cronbach’s alpha is frequently employed by researchers to assess reliability or the degree of consistency (Amirrudin et al., 2020). According to the analysis in Table 3, Cronbach's alpha values of for all constructs surpassed the limit of 0.7, with the majority nearing 0.9. Which indicates a strong level of internal consistency and reliability in measuring the variables (Zeller, 2005).

Table 3. Cronbach's alpha of constructs

Constructs	Cronbach's Alpha Value	No of Items	Internal Consistency
PU	.901	4	Excellent
PEOU	.879	4	Good
SI	.857	4	Good
TRUST	.889	4	Good
OIUAC	.898	4	Good

4.2. Regression Analysis

In quantitative studies, Petchko (2018) said, researchers frequently investigate the associations between several variables using observational data. Multiple regression is the preferred method for analysing such kinds of data. It allows researchers to get insight into the influence of different variables on a result and determine their relative significance. In order to evaluate the hypotheses, we utilised a regression model, with the millennials' intention to adopt eCommerce customer service chatbots as the dependent variable. Tables 4, 5, and 6 display the outcomes of the regression analysis, which include the values of the parameters, the degrees of relevance, and other statistical measures such as beta coefficients, T-values, significance levels, Tolerance, and VIF (variance inflation factor).

Here, the coefficient of determination or R^2 (R-Square) value is found .664, indicates that 66.4% of the total variance in the dependent variable can be explained by the independent variable in this model. An independent variable is considered to have a statistically significant effect on the dependent variable if the p-value is less than 0.05 (Thiese et al., 2016). Besides the adjusted R-squared value of 0.651 provides strong evidence for the accuracy of the regression model. The VIF and tolerance value are employed to identify and correct for multicollinearity (Senaviratna & A. Cooray, 2019). Based on the majority of research, a VIF value below 10 is considered acceptable to indicate low multicollinearity. According to Menard (2010), problems with collinearity can be indicated by a tolerance value below 0.2. Upon analysing Table 4, it is evident that the recorded values conform to the allowed limits for both VIF and tolerance. This indicates that the requirements for assessing multicollinearity have been met. We utilised the most rigorous criteria for VIF and tolerance to provide the most reliable measurements. Since all VIF values are within the acceptable range of 4 > VIF > 1 and tolerance values surpass the recommended level of 0.2, there is no need for any additional measures to address potential multicollinearity.

Table 4. Model summary

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	*F Change*	*df1*	*df2*	*Sig. F Change*
1	.815[a]	0.664	0.651	0.56365	0.664	53.274	4	108	0.000

a. Predictors: (Constant), TRUST_av, SI_av, PEOU_av, PU_av

Table 5. ANOVA analysis

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	67.702	4	16.926	53.274	<.001[b]
	Residual	34.312	108	0.318		
	Total	102.014	112			

a. Dependent Variable: OIUAC_av
b. Predictors: (Constant), TRUST_av, SI_av, PEOU_av, PU_av

Table 6. Coefficients output

Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics	
		B	***Std. Error***	***Beta***			***Tolerance***	***VIF***
1	(Constant)	0.236	0.252		0.936	0.351		
	PU_av	0.195	0.093	0.187	2.096	0.038	0.390	2.564
	PEOU_av	0.234	0.090	0.216	2.592	0.011	0.449	2.229
	SI_av	0.170	0.062	0.181	2.730	0.007	0.709	1.411
	TRUST_av	0.387	0.076	0.407	5.115	0.000	0.491	2.036

a. Dependent Variable: OIUAC_av

4.3. Test results of hypothesis

Hypothesis testing is a straightforward method to gather insights about a dataset and assess the validity of those insights (Kahl, 2023). Table 6 shows the results of hypothesis testing and also the statistically important relations between user attributes and their tendency towards using AI chatbots in eCommerce customer care. Notably, positive beta coefficients and p-values below 0.05 are found for Perceived Usefulness (PU, Beta = 0.187, p = 0.038), Perceived Enjoyment of Use (PEU, Beta = 0.216, p = 0.011), Social Influence (SI, Beta = 0.181, p = 0.007), and Trust in AI Chatbots (Beta = 0.407, p = 0.000). All four hypotheses proposing a positive influence on adoption intention were supported (Table 7).

Table 7. Hypothesis Results Output

	Hypothesis	Accepted / Not Accepted
Hypothesis1	The intention to use AI Chatbots is positively influenced by PU.	Accepted
Hypothesis2	The intention to use AI Chatbots is positively influenced by PEOU.	Accepted
Hypothesis3	The intention to use AI Chatbots is positively influenced by SI.	Accepted
Hypothesis4	The intention to use AI Chatbots is positively influenced by Trust.	Accepted

4.4. Discussion

Our analysis reveals that both perceived usefulness (PU) and perceived ease of use (PEOU) significantly contribute to explaining the variance in BI (behavioural intention) to use chatbots. The positive correlation between PU and OIUAC observed in this study reaffirms the conclusions of previous research conducted in many fields, including digital banking (O. T. Nguyen, 2020; Paramita & Hidayat, 2023; Raza et al., 2017), insurance platforms (De Andrés-Sánchez et al., 2023; Huang et al., 2019), the implementation of blockchain in financial applications (Kabir & Islam, 2021; Silva et al., 2023), and conversational agents (Goli et al., 2023; Soares et al., 2022). The influence of PEOU on OIUAC is stronger than that of PU, as indicated by beta coefficients of 0.216 and 0.187 respectively. This discovery is consistent with previous studies conducted in areas such as blockchain adoption (Kabir & Islam, 2021; Silva et al., 2023), intention to use digital banking (D. N. Nguyen et al., 2020; Raza et al., 2017), perception of conversational AI bots (Brachten et al., 2021; Kasilingam, 2020; Mostafa & Kasamani, 2022), and technology acceptance in insurance settings (Huang et al., 2019), where PEOU has been identified as a significant predictor of BI.

Regarding social influence, we have seen that its effect on millennials' OIUAC to utilise chatbots is significant. This is supported by existing research (Kabir & Islam, 2021; Kuberkar & Singhal, 2020; Melián-González et al., 2021; Trapero et al., 2020) that shows that people are more likely to embrace new technology when they receive favourable recommendations from their peers and influencers. This phenomenon is further exemplified by the extensive usage of various smartphone programmes, such as WhatsApp and Facebook, which have achieved substantial popularity due to positive SI (Kuberkar & Singhal, 2020).

rust was shown to be the most influential factor on OIUAC, as indicated by its greatest beta coefficient (0.407) in comparison to other factors. This is consistent with previous studies (De Andrés-Sánchez & Gené-Albesa, 2023; Kasilingam, 2020; Kuberkar & Singhal, 2020) that highlight the crucial importance of trust in influencing user perspectives towards AI chatbots. Aaccording to Kuberkar and Singhal (2020), like other online services, the extent to which consumers are willing to interact with a chatbot system depends on their perception of its trustworthiness, dependability, and reliability. Despite facing various challenges, chatbots possess substantial potential for augmenting the quality of customer care (Zhou, 2023). Our findings indicate that, when well executed, chatbots can provide significant assistance in the eCommerce field.

5. Conclusion

In the realm of eCommerce customer service, AI chatbots, although still new and in their developing stages (Kasilingam, 2020), possess considerable prospects as tools that can improve the delivery of customer services (Mohd Rahim et al., 2022). This study aimed to investigate the perceptions of millennials towards adopting customer service chatbots in eCommerce settings. It illustrates the persistent significance of the TAM (Davis, 1989) in explaining individual attitudes and intentions to use such technology. Our model explains over 65% of the variance in BI and establishes a robust qualitative framework. Results indicate that millennials' adoption of eCommerce chatbots hinges on PU, PEOU, SI, and Trust, with Trust and PEOU identified as primary influencers. Millennials perceive AI chatbots as beneficial for simplifying online purchases and enhancing the overall experience. The high user-friendliness of chatbots, reflected in PEOU, amplifies their appeal. Social influence from family, classmates, and coworkers significantly affects their acceptance. Trust emerges as a critical factor shaping their readiness to adopt this technology. These findings offer valuable insights for scholars and practitioners aiming to integrate chatbots into electronic commerce and other sectors.

5.1. Implications

This research empirically tests an extended Technology Acceptance Model (TAM) to understand behavioural intentions (BI) towards AI chatbots in customer service, showing that perceived usefulness (PU) and perceived ease of use (PEOU) positively influence intention to use these chatbots. While reaffirming TAM's relevance, especially in the context of AI chatbots in e-commerce, the study emphasizes the need for future research to generalize these findings across different technologies and contexts. The extended TAM, which includes trust and social influence (SI), explains 65.1% of the variance in adopting AI-based customer service chatbots in e-commerce, surpassing the original TAM's explanatory power of 40% (Venkatesh and Davis, 2000). Incorporating external variables such as trust and SI enhances TAM's ability to predict technology adoption, aligning with prior research (Taylor and Todd, 1995; Bhattacherjee 2002); and Pavlou et al, 2003). These insights are particularly valuable for businesses implementing or considering chatbots for e-commerce customer service, with broader implications across sectors like healthcare and education (Caldarini et al., 2022). While emphasizing PU and PEOU remains crucial, building trust is equally important. Beyond data security and interface clarity, fostering genuine trust involves transparent practices and authentic user experiences, avoiding over-reliance on potentially biased online reviews or endorsements from social influencers motivated by financial gain.

5.2. Limitations and recommendations for further research

This study acknowledges several limitations that call for further investigation. The reliance on a convenience sampling strategy, primarily through professional networks on LinkedIn, introduces a potential bias towards a homogenous sample. The majority of participants were young males (26-30 years old). Future research should employ more robust sampling methods, such as random sampling, to ensure representativeness and generalizability of the findings. Building upon Chung et al. (2020), this study focused on participants with prior chatbot experience. However, investigating chatbot adoption among individuals with limited or no digital assistant experience would provide valuable insights. While this study offers valuable information regarding millennial adoption intentions for eCommerce chatbots, the generalizability of findings is limited due to the specific generational focus and relatively small sample size. Exploring chatbot adoption across different age groups is crucial to understanding the varying perceptions and attitudes towards this technology. The research primarily investigated technology-related aspects, potentially overlooking other significant factors influencing chatbot adoption. Future studies should consider broadening the scope to encompass socio-cultural, technical, socio-economic, and legal dimensions for a more holistic understanding. Finally, the timeframe of the study might have restricted a more in-depth examination of specific concerns or the collection of additional data. Nevertheless, this research serves as a valuable foundation for future investigations into the adoption of this emerging technology.

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