Volume 2, Issue 2, 2026, Pages 072–083
| Regular Article | Open Access

Journal of Digital Business and International Marketing

Understanding User Satisfaction with E-Commerce Chatbots in Vietnam

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Article Info
Journal of Digital Business and International Marketing
https://www.ansispublications.com/journals/jdbim/jdbim.html

https://doi.org/10.64026/JDBIM/2026008

Received 02 November 2025.
Revised from 02 January 2026.
Accepted 18 January 2026.
Available online 05 April 2026.
Published by Ansis Publications.

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Abstract – We review the factors influencing user satisfaction in AI-based chatbots on online shopping websites, focusing on utilitarian, hedonic, technological, and social gratifications, social influence and perceived privacy threats. Using survey data of 1,007 respondents spread throughout Northern, Central, and Southern areas of Vietnam, the constructs were operationalized by using validated reflective measures and then analyzed using PLS-SEM. The empirical findings demonstrate that the following types of gratifications, utilitarian, hedonic, technological, and social gratification, along with social influence, are significant contributors to user satisfaction, and perceived privacy risks do not play an important role. The results presented highlight the significance of social and experience elements in the interactions of chatbots with e-commerce, and these findings can be applied practically to the development of AI-based systems that can improve engagement, trust, and loyalty among young, digitally-savvy consumers.

Keywords – AI Chatbots, E-Commerce, User Satisfaction, Gratification Theory, Social Influence, Privacy Risks, Partial Least Squares Structural Equation Modelling.

I. INTRODUCTION

Chatbots are flexible and have a significant potential. The human service personnel are often forced to deal with the boundaries of their knowledge; they might experience difficulties in managing various organizational resources, and they might feel tired [1]. Chatbots are accessible 24 hours, and due to the scalability technology, clients can access it without any waiting period. As a result, they have significant potential to reduce costs and automate the processes in the enterprises.

Well-known chatbots, including Apple Siri, Amazon Elexa are common knowledge, and the employment of chatbots as tools to address various tasks is on the rise. The first example is the IBM question-answer framework, referred to as Watson. Chatbots are not only applied in IT firm but can be used elsewhere. In 2020, more than 85% of client contacts were arranged via different types of chatbots. As an example, external communication (such as by companies communicating with their customers through chatbots) is one area that businesses may use chatbots; however, internal communication (business-to-business) is another area where chatbots can be used. Large companies often use chatbots as recruitment, employee support, and training, the example of Meet Frank is an anonymous chatbot, which helps to introduce talent to businesses. Communicating with clients through Live-Chat interfaces has become a common practice to provide real-time client service in a number of settings, among which is e-commerce.

AI-based Chatbots facilitate the dialogue through Natural Language Processing (NLP) with the help of text or voice. They offer 24/7 availability, thus improving the engagement of the customers and the performance of the business. Chatbots provide pertinent responses after interpreting user messages in natural language and can handle multiple users at once. They frequently employ the first-person narrative, including such pronouns as I, or they also use the names of users to make the conversation feel more realistic and, therefore, establish a feeling of association and trust. However, there are still a number of chatbots that are still below the expectations of consumers. Since human communication is inherently social in nature, the chatbot should be designed in a way that takes into account social aspects to enhance interaction [2].

AI chatbots have now become a common feature in customer service, providing real-time responses to requests and solving issues in real time. This does not only improve the level of customer satisfaction through reduction of wait time but it also helps organizations to facilitate more clients contact without extra expenses. Data analytics also enable companies to understand client behavior thus enabling them to tailor their services to meet their individual needs and interests. This level of personalization is very welcomed by the customers and can lead to satisfaction in improved level. The latest developments, including blockchain and IoT, have significantly enhanced transparency and monitoring of the product condition along with the traditional technologies in the field of logistics. blockchain offers safe non-mutable leads concerning delivery data and thus helps alleviate the problem of trustworthiness and responsibility.

Digital technology and growth of e-commerce have significantly changed the behavior of customers and transformed the retail environment. Development of electronic commerce has made online shopping an essential part of everyday life in various countries, which is mostly explained by the high number of advantages connected with the convenience of the process of buying products. However, with digitization, there are not only the economic activities that are carried out exclusively through the online platform, but also the activities that involve online and offline options. The retail industry is increasingly implementing omni-channel solutions and provides the customer with numerous alternatives, including online shopping and webrooming (researching online and making a purchase offline) [3].

In this study, we focus on analyzing the effect of using AI-powered chatbots and their effect on the satisfaction of users in online stores. In particular, we examine the impact of hedonic, utilitarian, technological, and social gratifications, social influence, and perceived risks of privacy on the way customers assess chatbot interactions. Based on these deliberations, the research is able to draw six main hypotheses:

- *H1:* Higher utilitarian gratification, or the practical and functional advantages of chatbot interactions, will result in the higher satisfaction of users.
- *H2:* It is assumed that hedonic gratification, which can be described as delight and enjoyment associated with the communication with chatbots, impacts positively on user satisfaction.
- *H3:* Technological gratification, which entails perceptions of innovation, system intelligence, and performance, is likely to boost user satisfaction.
- *H4:* The social gratification, which is a measure of the perceived social presence and the quality of the conversation with the chatbot, is theorized to have a positive impact on the satisfaction.
- *H5:* Perceived privacy risk is assumed to be a possible negative determinant of user satisfaction.
- *H6:* Social influence as a factor, which is the influence exerted by the peers and social networks, is hypothesized to have a positive influence on the user satisfaction.

These are the hypotheses that help to develop the conceptual basis of the empirical analysis that will be provided in the following sections. All of them are indicators of functional and social determinants of satisfaction within the context of AI-mediated e-commerce interactions.

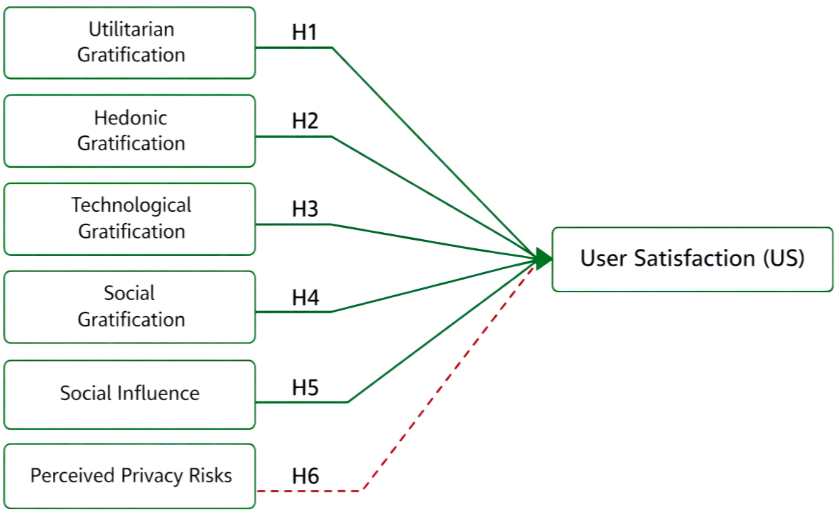

Fig 1. Conceptual Model.

Fig. 1 presents the conceptual model that will be used in this study, where six independent constructs are integrated. These include social influence, social gratification, technological gratification, hedonic gratification, utilitarian gratification, and perceived privacy risks that are expected to affect the dependent variable, which is user satisfaction. The rest of the paper is structured in the following manner: Section II reviews related works on uses & gratifications in AI chatbots, social influence on technology user, and perceived risk and trust online. Section III describes the samples, study design, and data sources, including measurement model evaluation construct measurement, and formulation/estimation of structural model.

Section IV provides a detailed discussion of our findings. Lastly, Section V concludes our study and highlights the relevance of user satisfaction in AI-based chatbot communication in e-commerce websites.

II. RELATED WORKS

Uses & Gratifications in AI Chatbots

Quan-Haase and Young [4] reviewed the Uses and Gratification Theory (U&G) as a communication theory that is a foreground of social interactions. This theory has a functionalist perspective on communication and media that assume that the main role of media is to fulfil the needs and interests of the viewers. The satisfaction of these needs, therefore, results in the increase of pleasure. Happiness and gratification are based on two main questions:

1) What prompts people to use specific media?
2) What is the kind of pleasure that media can provide people?

The first method is analyzing the motivations of the audience followed by determining the message and the social structure. The theory is concerned with the media-seeking behavior of the consumers and their satisfaction with the type, content, and the process of using media. The two stated questions in U&G would eventually resolve the good and bad outcomes associated with using certain type of media.

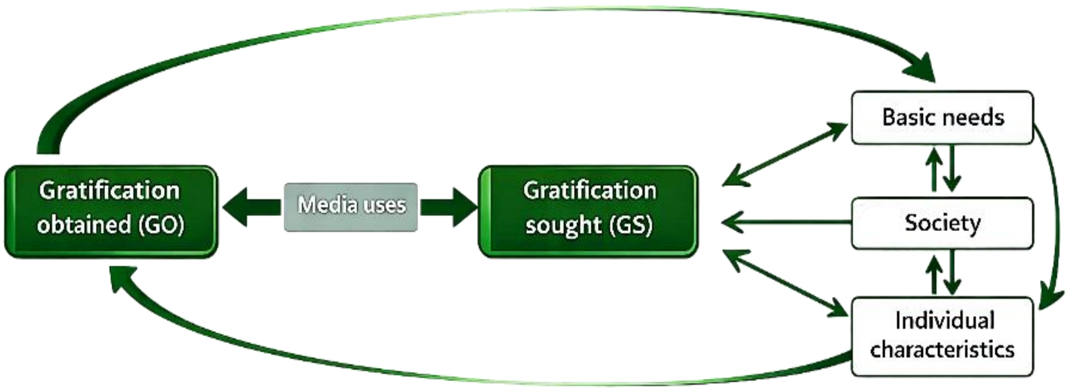

Fig 2. Streamed R&G Model.

The Uses and Gratifications (U&G) theory in **Fig. 2** was extended by Xie, Wang, and Cheng [5] to investigate the acceptability of artificial intelligence (AI) chatbots by consumers to online shopping in China. A questionnaire was conducted online on 540 participants, and all reported to actively use online commerce and being aware of chatbot technology. The ensuing data analysis offered empirical evidence of the hypothesis that utilitarian (e.g., perceived authenticity of conversation and convenience) and hedonic (e.g., perceived enjoyment) factors have a positive effect on the positive attitude of consumers towards the use of chatbots. Nonetheless, privacy challenges and the comparatively underdeveloped nature of the technology were cited as it gave rise to major discouraging factors.

According to Zadeh et al. [6], a UGT approach has been recently embraced as a way of predicting consumer behaviors pertaining to incentives to use social media platforms. In these platforms, the brands have a clear goal of engaging audiences by providing them with value or satisfaction through the content. In this regard, the content should be designed in a way that it offers certain value to the intended customers, thus contributing to greater engagement and desired results. In the recent literature [7], which explores consumer decision making in online and social media traditions, constructs based on UGT, such as the desire to socialize, be entertained, seek and share information, and obtain a reward or remuneration, have been studied.

Social Influence on Technology Use

Social influence has been empirically established to directly influence the intention of users in a context of compulsory usage and directly impact the view of the users in a context of voluntary usage. Besides, Assefa and Frostell [8] have noted that there are different degrees of social impact when comparing different technologies being studied. In the consumer milieu, social influence has taken antagonistic roles. An example is that a number of studies have also established a direct positive implication of social impact on the intention to use technology. Further studies have reported a positive direct effect of social processes on attitudes of customers.

As described by Graf-Vlachy, Buhtz, and König [9], social dynamics have a significant effect on human behavior especially in the context of the adoption of information technology, which has attracted the attention of a number of scholars. Conceptualization of social influence is seen as the change in the beliefs, emotions, attitudes, or actions of one individual and is caused by the interaction with another individual, or a group of individuals who are perceived as similar, desirable or authoritative. Social influence has been known to have a role in information systems research as the inter-personal considerations of technology adoption and usage, with that decision often being made collaboratively, or with consideration of how they affect or meet the needs of others or groups.

Holtgrewe [10] argued that since information and communication technologies (ICT) are increasingly turning into an element that cuts across every aspect of the modern lifestyle, the question of the factors that affect the choices of people to accept and use these technologies has been of immense importance. The prevalence of innovative technologies, especially social ones, can indicate that social influence can become the primary determinant of the success of such systems. Based on this, scholars and practitioners should understand the impact of social influence in the implementation of technology.

Perceived Risk and Trust Online

The online retail setting has unique features that lead to a perceived threat by the consumer, unlike the physical retail setting. Perceived risk is a significant interference to the development of ecommerce and is a detrimental factor to its potential to serve as a long-term source of competitive advantage in organizations. However, in B2C, Chiu et al. [11] also noticed that the perceived risk increases to the detriment of the utilitarian value and enhances the impact of hedonic significance on the intention to repurchase.

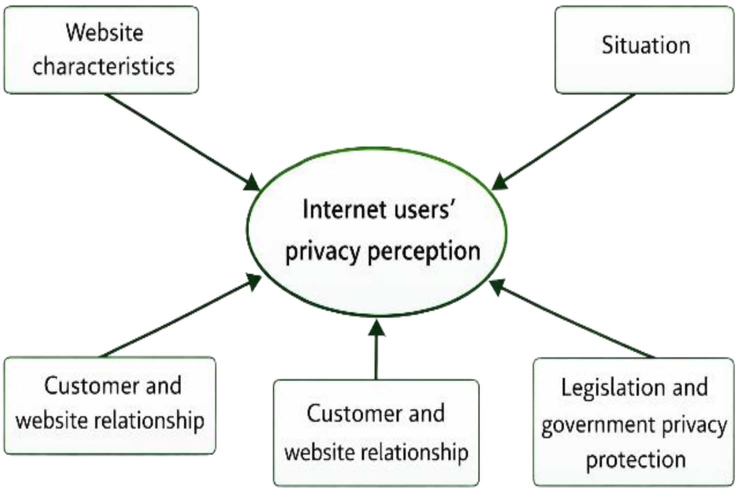

Fig 3. Influences on Internet Privacy Awareness Among the Users.

Many factors are behind the unwillingness of buyers to purchase items on the websites, as shown in **Fig. 3**; however, studies have shown that one of the major reasons is lack of trust. Corporate credibility which includes human trustworthiness and knowledge refers to the degree to which a company meets the expectations of customers when it comes to products and services provision.

Hirunyawipada and Paswan [12] recognizes four types of perceived risk namely, technological risk, vendor risk, customer risk, and product risk. The perceived technological risk is described as the level of perceived loss by consumers to potential losses brought about by internet and its technological infrastructure with respect to slow downloads, inability to search, or potential weaknesses in security. Vendor perceived risk is the dimension to which consumers perceive that online purchases can cause losses that can be attributed to the internet vendors including failure to deliver goods and misuse personal information. In case the clients purchase goods or services via chatbots, they run a risk to find themselves in a dangerous situation of privacy breaches in case of misuse or leakage of personal data, including phone numbers, names, or addresses, to third parties. The negative implications of privacy threat on user happiness have been researched.

Miyazaki and Fernandez [13] proved that the privacy and security worries can reduce the consumer happiness in the online environment. Since chatbots are commonly used in both corporate communication and online transactions, it can be assumed that the perceived threat to privacy of clients about corporate chatbots can decrease their satisfaction with chatbot services.

III. DATA AND METHODS

Sample, Study Design and Data Source

This research employs primary survey data of the respondents with previous experience of using AI-powered chatbots in online shopping platforms. Survey data was collected using a designed online questionnaire that was distributed to the North, Central, and Southern parts of Vietnam to reflect the heterogeneity of the region in relation to digital consumption behaviors. Complete, consistent, and quality responses were filtered to come up with a final dataset that comprised 1,007 valid observations. The sample is vastly represented by young adults who are highly active online shoppers utilizing chatbots, which is the demographic profile that will accommodate the goal of the study to explore the development of satisfaction in AI-mediated e-commerce relationships.

The size of our sample was evaluated with the desired SEM (structured equation modelling) requirements to ascertain the level of sufficiency of the dataset in conducting a multivariate analysis. The number of observations was sufficient to estimate a structural model with multiple latent predictors with a minimum number. The sequence of methodological decisions that will direct the screening of the data, inclusion criteria and the readiness to analyze the data will be presented in a methodological flowchart (see **Fig. 4**) describing every decision node and validation step, which will be included in the final version of the manuscript.

Measurement Model Evaluation Construct Measurement
All constructs of the study were modeled as reflective latent variables, which were measured through many observed indicators. The adapted version of validated instruments that were used as measurement items in the previous literature guaranteed a theoretical consistency and content validity. The extent of agreement with every statement was measured using a five-point Likert scale hence the responses were taken.

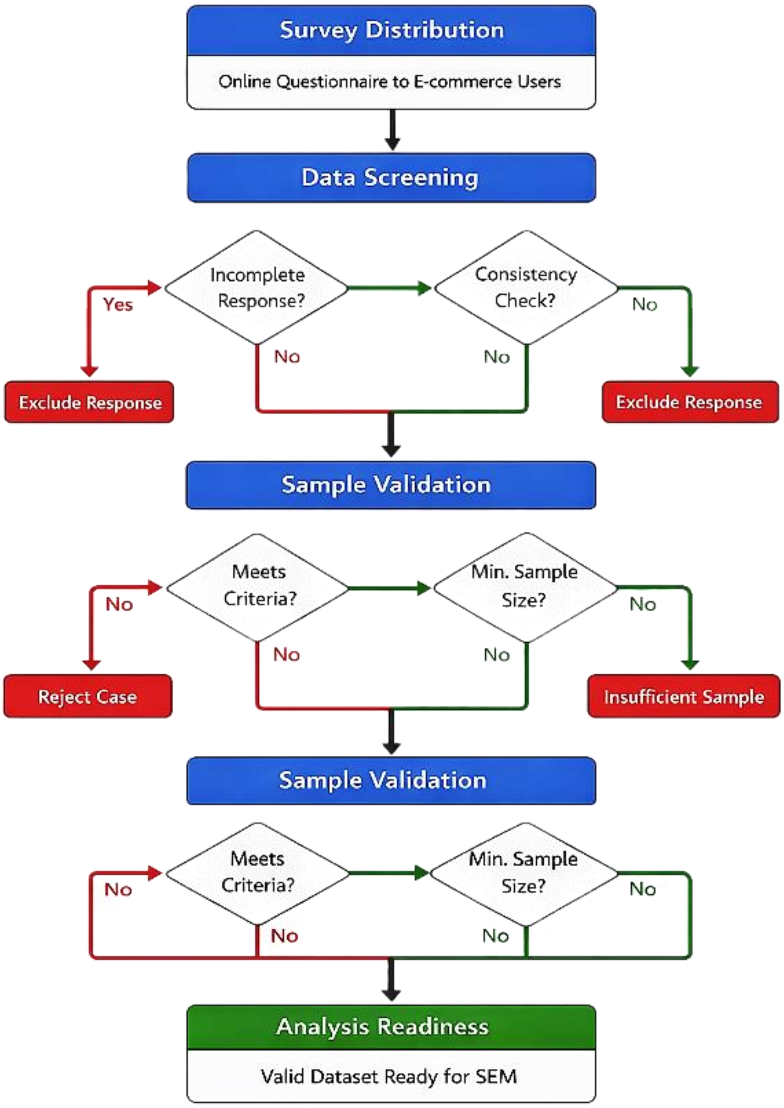

Fig 4. Workflow in Data Collection.

The observed indicator of latent construct x_{ij} is denoted by i and j. The relationship of the reflective measurement can be stated using Eq. (1).

$$x_{ij} = \lambda_{ij}\eta_i + \varepsilon_{ij} \tag{1}$$

with λ_{ij} representing the factor loading, η_i representing the latent construct, and ε_{ij} representing measurement error. Internal consistency reliability (ICR) was tested through a number of coefficients; the α of Cronbach was calculated using Eq. (2).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{j=1}^{k}\sigma_{x_j}^2}{\sigma_T^2}\right) \tag{2}$$

where k refers to the number of indicators, $\sigma_{x_j}^2$ distorts the variance of indicator j, and σ_T^2 distorts the overall variance of the construct. In order to calculate composite reliability, we employed Eq. (3).

$$CR = \frac{\left(\sum_{j=1}^{k} \lambda_j\right)^2}{\left(\sum_{j=1}^{k} \lambda_j\right)^2 + \sum_{j=1}^{k} \theta_j} \tag{3}$$

where, θ_j is indicators error variance. Evaluation of CR (convergent validity) was achieved by computing AVE (average variance extracted) using Eq. (4).

$$AVE = \frac{\sum_{j=1}^{k} \lambda_j^2}{\sum_{j=1}^{k} \lambda_j^2 + \sum_{j=1}^{k} \theta_j} \tag{4}$$

The concept of discriminant validity (DV) was tested by employing F-L (Fornell-Larcker) methodology, which necessitates that the AVE's square root of constructs should be more than its inter-construct relationships. The overall reliability/validity measurement chain, including predetermined acceptance levels and re-specification guidelines, is illustrated in a measurement evaluation workflow (see **Fig. 5**), which is mentioned in the present paper in order to guarantee methodological transparency.

Strategy of Formulation and Estimation of Structural Models

After the validation of the measurements, structural relationships between latent constructs were estimated based on Partial Least Squares Structural Equation Modelling (PLS-SEM). This approach was chosen because it is strong in dealing with complex models, non-normal data distribution and the research objectives of prediction.

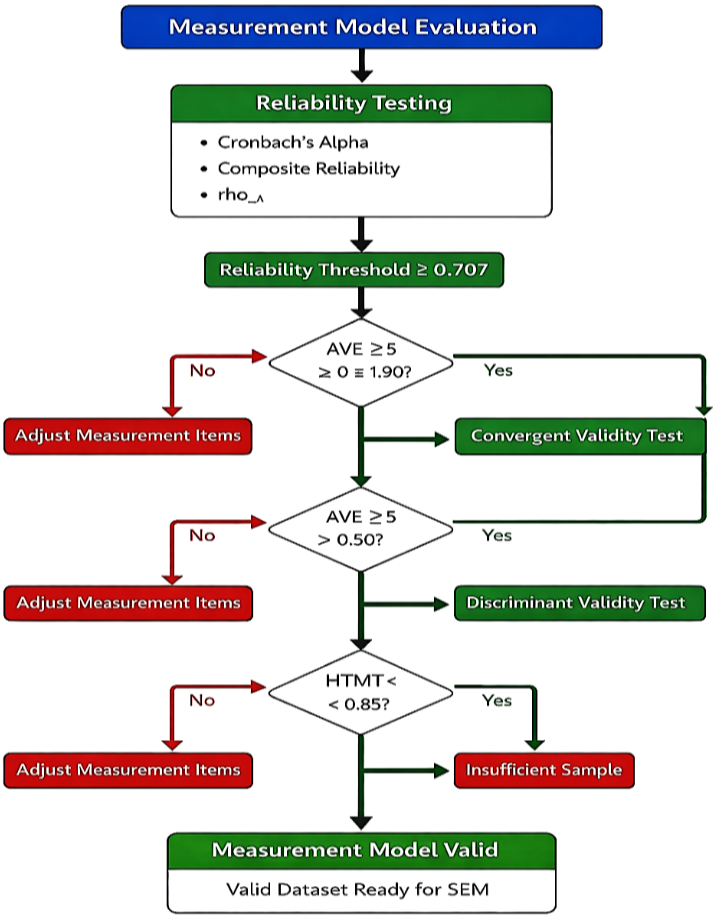

Fig 5. Evaluation of the Measurement Model.

User Satisfaction was considered the endogenous construct under the impact of the gratification dimensions, privacy threats and social impact, and the structural model is modeled using Eq. (5).

$$US = \beta_1 UG + \beta_2 HG + \beta_3 TG + \beta_4 SG + \beta_5 PR + \beta_6 SI + \zeta \quad (5)$$

in which β_i is the structural path coefficients and ζ is unexplained variance. The Variance Inflation Factor in Eq. (6) was used to test collinearity between constructs of predictors and the value.

$$VIF_i = \frac{1}{1-R_i^2} \quad (6)$$

where R_i^2 has been obtained by regressing the predictor on all the other exogenous constructs. VIF values were all in acceptable values, thus, collinearity did not affect the stability of the estimation.

A non-parametric bootstrapping test of 1,007 resamples was used to test the hypothesis. Bias-corrected and accelerated confidence intervals were applied when statistically testing the significance. The t-statistic of each structural path was worked out to using Eq. (7).

$$t_i = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)} \quad (7)$$

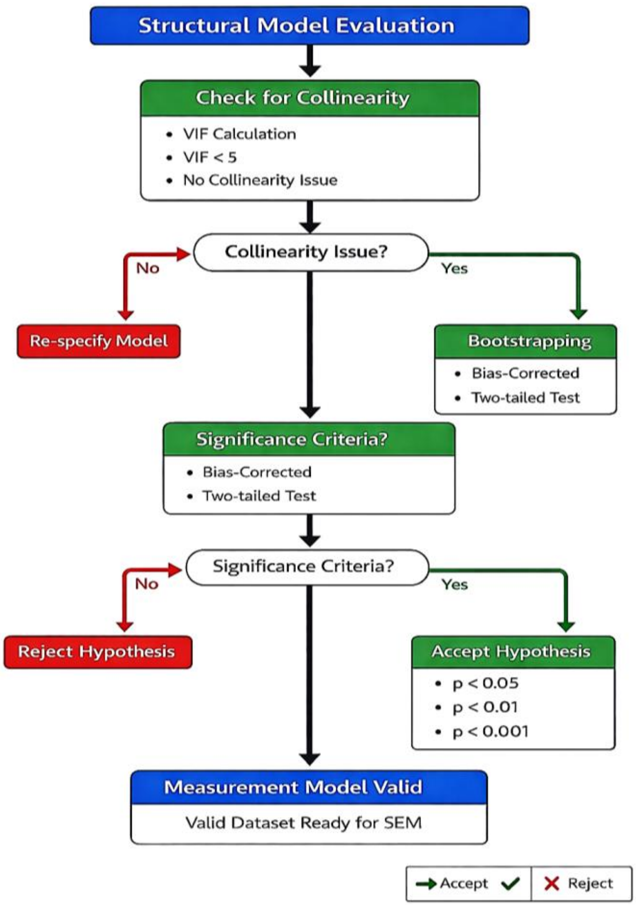

Fig 6. Structural Model Analysis.

$SE(\hat{\beta}_i)$ represents the bootstrapped standard error. The paths were deemed statistically significant when the respective p-value was less than the standard $5.745 = 0.05$. The rationale behind the evaluation of the hypothesis, such as decision limits and acceptance level, is presented in a structural decision flowchart in **Fig. 6**.

IV. RESULTS AND DISCUSSION

The target population of the survey participants is provided in **Table 1**. Among the participants, 37.60% were male, and 62.41% were female. The greatest age group was comprised of the individuals aged between 18 and 23 (61%), then the aged between 24 and 30 (39%). Earnings per month were grouped into various categories: 15.5% earned 5 million VND, 32.2% earned 6 million VND, 35.7% earned 11 million VND, and 16.71% had an income of more than 11 million VND. The sample was a representative sample comprising of a diverse population of educational levels: 6.30% PHD, 8.31% master degree, 53.70% bachelor degree, 13.72% college, 7.11% intermediate training, and 10.90% high school.

Table 1. Overview of the Sample

Analytical dimension	Key distribution patterns (frequency; %)
Gender composition	62.41% (628) Female · 37.60% (379) Male
Age structure	18–23 years: 614 (61.0%) · 24–30 years: 393 (39.0%)
Income range (monthly)	6–11 million VND: 359 (35.7%) · 2–6 million VND: 324 (32.2%) · Over 11 million VND: 168 (16.7%) · Under 2 million VND: 156 (15.5%)
Educational attainment	University: 541 (53.7%) · College: 138 (13.7%) · High school: 110 (10.9%) · Master: 84 (8.3%) · Doctor: 63 (6.3%) · Intermediate: 71 (7.1%)
Geographical distribution	South: 385 (38.2%) · North: 327 (32.5%) · Central: 295 (29.3%)
E-commerce platform preference	Shopee: 371 (36.8%) · Lazada: 233 (23.1%) · Tiki: 218 (21.6%) · Taobao: 52 (5.2%) · Sendo: 48 (4.8%) · Other: 54 (5.4%) · Amazon: 31 (3.1%)

Of all the respondents, 32.5% of the participants were found in the North, 29.3% were found in the Midwestern and 38% were found in the South. Shopee had been used by 36.8 per cent of respondents as well as Tikia 21.6, Lazada 23.1, and other sites, Taobao, Sendo, and Amazon, formed the other 18.5%.

The dataset contains descriptive statistics of a great number of important parameters. Utilitarian Gratification (UG) scale showed low response variability with the mean being 3.80 with SD of 0.90. The higher and more stable measure of satisfaction is the Hedonic Gratification (HG) which has an average of 3.85 with a SD of 0.771. The average of TG (technological gratification) rating is 3.78 and 0.72 SD. The level of contentment in SG (social gratification) has been constant, showing mean score of 3.87 and 0.761 SD. The respondents had a moderate degree of consensus with a mean Privacy Risks (PR) of 3.97 and a standard deviation of 0.68. An average of 3.78 and SD of 0.86 on SI (social influence) show that there is a great deal of heterogeneity in the responses.

The level of customer satisfaction in the United States is very high with a 3.92 average and a 0.75 SD. It can be concluded that the digital services under evaluation have fulfilled the satisfaction of the respondents generally. A critical analysis is given in **Table 2**.

Table 2. Data Analysis

Construct Code	Observed Construct	Mean Score	SD
PR	Privacy Risks	3.97	0.68
SI	Social Influence	3.78	0.86
HG	Hedonic Gratification	3.85	0.77
UG	Utilitarian Gratification	3.80	0.90
TG	Technological Gratification	3.78	0.72
SG	Social Gratification	3.87	0.76

The details of the assessment of ICR are represented in **Table 3**. The attainment of ICR was when the Cronbach alpha, Dijkstra-Henseler's rho_ A, and composite reliability were above the 0.70 mark (77). Moreover, convergent validation was checked by making sure that all constructs had an AVE value of greater than 0.51. In addition, the justification of the DV is supported with the help of the application of the F-L methodology as **Table 4** shows. The AVEs square roots of all constructs are higher than the inter-construct highest correlations. In turn, the data in each construct show more association with the particular construct in question than any other, as shown by this detailed analysis. These results also support the validity and reliability of the method of measuring.

Table 3. Data on Validity as Well As Reliability

Indicator	UG	HG	TG	SG	PR	SI
Cronbach's alpha	0.911	0.913	0.856	0.882	0.839	0.880
Composite reliability	0.924	0.914	0.888	0.883	0.849	0.891
Rho_A	0.933	0.931	0.897	0.914	0.885	0.911
AVE	0.736	0.658	0.636	0.680	0.607	0.682

Table 4. Discriminant Validity

Construct	1	2	3	4	5	6	7
1. HG	1.000						
2. PPR	0.568	1.000					
3. SG	0.868	0.545	1.000				
4. SI	0.861	0.514	0.830	1.000			
5. TG	0.795	0.465	0.827	0.740	1.000		
6. UG	0.976	0.575	0.806	0.886	0.677	1.000	
7. US	0.764	0.540	0.842	0.766	0.765	0.801	1.000

The structural model was further tested after a comprehensive test of the measurement models. An initial test of multicollinearity was done through analysis of inner variance inflation factor (VIF). It is worth noting that except the highest value of 3.908, all other VIF estimates have not surpassed the traditional value of five thus suggesting that the analysis was not affected by collinearity.

Table 5. Model Estimations

Hypothesis	Structural Path	p-value	t-value	Path Coefficient	Decision
H1	UG → US	0.000	4.379	0.134	Supported
H2	HG → US	0.000	5.627	0.207	Supported
H3	TG → US	0.004	2.926	0.087	Supported
H4	SG → US	0.003	3.827	0.140	Supported
H5	PR → US	0.192	1.305	0.034	Not Supported
H6	SI → US	0.000	10.231	0.366	Supported

Therefore, the effect of multicollinearity was not brought into the results. Then, statistically significant and relevant relations of the structural model were tested through the resampling method with 1,007 samples with acceleration and bias modification with a dual-tail hypothesis test added to it. These estimations are shown in their entirety in **Fig. 7** and **Table 5**. The analysis indicates that there are different levels of relationship in the various constructs. The study pinpointed a number of significant and positive relationships with other areas of user happiness. The results suggest that H1 is supported because utilitarian pleasure plays a major objective of enhancing user experience with chatbots engagement on e-commerce sites.

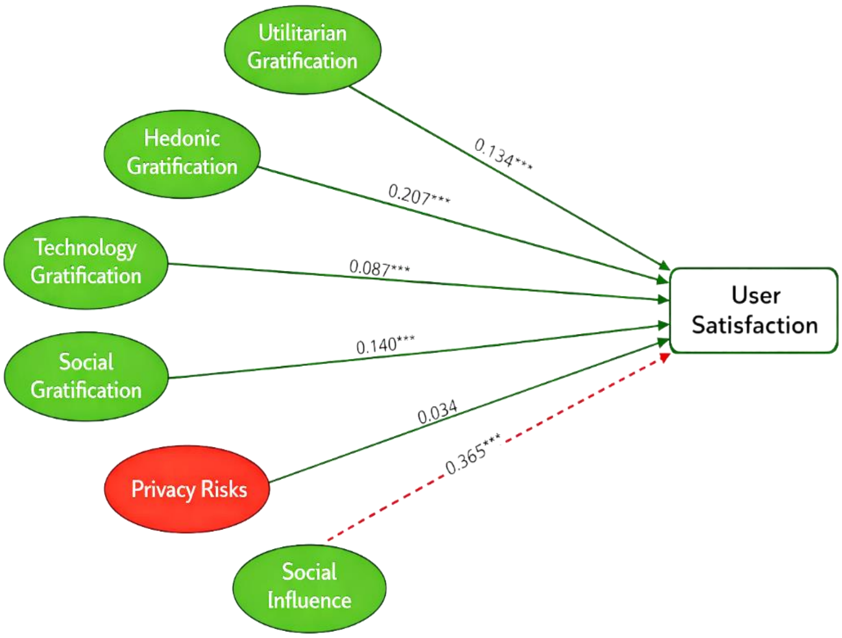

Fig 7. Estimated Model.

The statistics indicate that individuals who obtain utilitarian gratification (by attaining practical goals and retrieving data) express a high level of contentment. This finding increases the previous literature that reported that the perceived usefulness of AI-based chatbots positively affects the levels of user satisfaction. The hedonic gratification is a strong driver and therefore the idea is that consumers who experience pleasure after using chatbots would have a high level of happiness; therefore, H2 is well proved. The findings are meaningful to the usefulness of enjoyable and emotionally satisfying interactions as shown by research studies by Liaw and Huang [14].

People who derive enjoyment and enjoy the communication with chatbots display better overall satisfaction, which proves the critical importance of hedonic experiences. The technological gratification can contribute greatly to the user pleasure which supports H3 and underlines the role of technological factors in the development of the user experience. A favorable correlation between technological pleasure and user happiness is also found by Spahn [15]. The growing number of internet customers in an unstable business environment has made the companies deliver outstanding customer services. However, with the emergence of AI-powered chatbots, people have provided effective remedies to their advertisement issues and have allowed companies to connect with customers by means of enhanced customer service experiences. In turn, one should better understand the factors that increase customer pleasure and the experience using the chatbot.

It has been shown previously that utilitarian pleasure, social gratification, and hedonic gratification are major user gratifications, which have positive impacts on user attitudes and increase their trust in the new technology. Utilitarian satisfaction, e.g., will help chatbot clients to receive the relevant insights and increase customer fulfillment. Hedonic pleasure is the level to which the consumers are emotionally supported by the engagements and amusement thus enhancing the technological experience. Social satisfaction facilitates interactions between chatbot clients and their social dynamics, increasing the level of confidence of users and rendering the chatbot experience based on AI technology more fertile. In addition, studies have indicated that technological competencies including emotional skills, cognitive skills and relational skills are contributing factors to user pleasure with technology. In this research, the competencies are conceptualized to examine user happiness and chatbot usability.

Social pleasure has a strong influence on user experience in chatbot engagement on e-commerce sites, thus supporting H4. This result demonstrates the positive effect of social gratification on the happiness of users as it implies that the user, who is appreciative of social interactions enabled by chatbots, will be more satisfied with their user experience, as other researchers (such as Cheng and Jiang [16]) also have. It shows that promoting a social engagement environment in the e-commerce sites improves user experiences. Our results regarding pleasure correspond with the findings of Hsu and Lin [17] who describe that the user gratification with chatbot service is significantly related to four important areas: social, technical, hedonic, and utilitarian fulfillments.

Social impact has been considered as a major contributor to customer satisfaction. The study demonstrated that social impact is a major element that determines the level of user happiness when interacting with a chatbot on e-commerce websites since the path coefficient of social impact is 0.366, thus supporting H6.

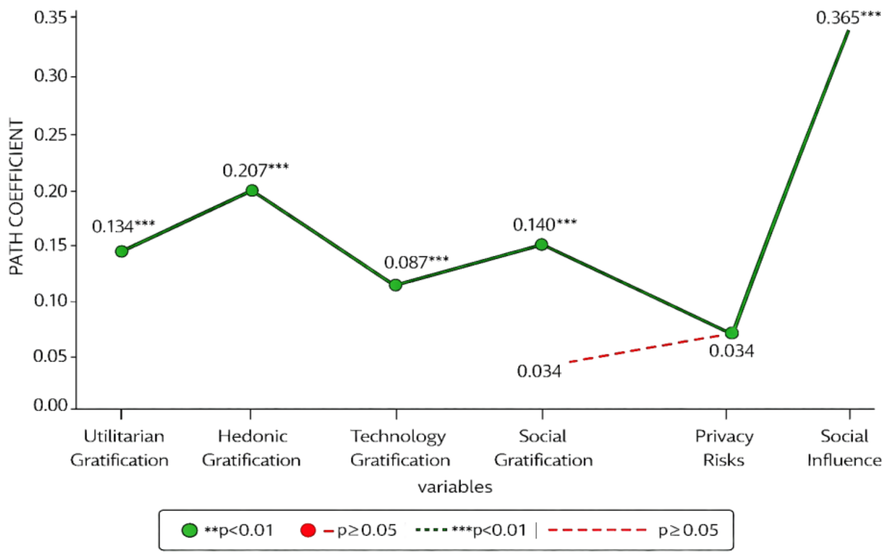

Fig 8. Approximated Path Coefficients Between Variables.

Among the six criteria that were studied within the framework of the research, social impact (SI) turned out to be the greatest predictor of customer satisfaction with AI-driven chatbots on e-business websites in Vietnam (see **Fig. 8**, ***p < 0.001, **p < 0.01). The findings are in correspondence with the findings of Dunne, Lawlor, and Rowley [18]. Their research contributes to the significance of social networks in stimulating the views and pleasure of young users. Such conclusions are in line with the conclusion drawn by Vohra and Bhardwaj [19], hence depicting the applicability of peer engagement in the e-commerce industry.

Those who are affected by social conditions and, in particular, those who are supported with the help of chatbots, provide high levels of satisfaction, which proves the critical role of social factors in ensuring full customer satisfaction. This outcome in Vietnam could be explained by the fact it has a collectivist society and people tend to follow group norms, perspective and shared experience rather than personal preferences. The use and interaction with new technologies like chatbots is influenced to a great extent by the peers, relatives, and social networks in young people. This cultural divide shows the significance of social influence where judgements are usually influenced by the views or recommendation of others about a certain idea. Additionally, the young potential consumers are typically involved in social media such as Facebook where tech insights and peer communication are common.

The societal impact of the societal media is augmented through the rapid access/delivery of encounters with the chatbots and, as such, increases trust and acceptability. The result highlights the significance of e-commerce sites to work tactically in using social impact to enhance consumer happiness and adoption levels especially in a socially dynamic country like Vietnam. Nevertheless, discussing the conceptual framework, it is fundamental to consider that H5 that determines the direct effect of privacy concerns on user satisfaction is not supported. We obtained a 0.192 p-value, which is statistically not significant implying that there is no adequate data to prove stronger direct effect in this scenario. This observation is in stark contrast with most of the earlier studies that have attributed privacy issues to user pleasure such as the ones done by Kokolakis [20]. This surprising finding can be explained by a number of variables.

First, teenagers are technologically more skilled and knowledgeable about shopping systems on the Internet. Their experience of revealing personal data to the digital services including e-commerce service providers, and social media is one that is expected to reduce their anxieties about privacy risks. Several AI-driven chatbots have been integrated into key e-commerce apps like Shopee, Lazada and Tiki, in addition to major banking organizations, in Vietnam. Users often assume that such platforms will handle their personal data in a responsible manner, which will minimize the anxieties about privacy. Moreover, younger users are more likely to focus on the specific functional benefits, such as convenience and efficiency, and affective benefits, such as enjoyment, linked to the use of chatbots and tend to take them at the cost of more abstract concerns about data security.

Accordingly, the apprehension towards the risk of privacy disclosure was relatively lower among the respondents in respect to the disclosure of financial and payment details to chatbots. Though privacy related issues do not significantly influence the overall satisfaction, they cannot be overlooked by e-commerce companies and banks. Clearly revealing the habits of data use and enforcing effective security measures can foster a long-term sense of trust, especially as more people recognize the problem of privacy.

V. CONCLUSION

The study provides empirical data on the factors that drive user satisfaction in AI-based chatbot communication in e-commerce websites. Utilitarian, hedonic, technological and social gratifications were also identified to significantly increase satisfaction, which supports the critical role of functional, emotional and social benefits that chatbots bring to positive user experiences. Social influence proved to be the strongest predictor, which shows the role of peer networks and collective norms in the perception of technology adoption in the Vietnamese setting. In contrast to the hypotheses, perceived privacy risks did not show a substantial influence on the level of gratification, which may be defined by the fact that users become accustomed to using digital platforms and rely on the level of trust in well-known services. These findings provide practical information to e-commerce operators who seek to optimize chatbots, focus more on engagement, functionality and socially enhanced user experiences as avenues to greater satisfaction and adoption.

CRediT Author Statement
The author reviewed the results and approved the final version of the manuscript.

Data Availability
No data was used to support this study.

Conflicts of Interests
The author declares that they have no conflicts of interest.

Funding
No funding agency is associated with this research.

Competing Interests
There are no competing interests.

References

[1]. X. Wang, X. Lin, and B. Shao, "Artificial intelligence changes the way we work: A close look at innovating with chatbots," Journal of the Association for Information Science and Technology, vol. 74, no. 3, pp. 339–353, Jan. 2022, doi: 10.1002/asi.24621.
[2]. A. P. Chaves and M. A. Gerosa, "How Should My Chatbot Interact? A Survey on Social Characteristics in Human–Chatbot Interaction Design," International Journal of Human–Computer Interaction, vol. 37, no. 8, pp. 729–758, Nov. 2020, doi: 10.1080/10447318.2020.1841438.
[3]. M. Yrjölä, M. T. Spence, and H. Saarijärvi, "Omni-channel retailing: propositions, examples and solutions," The International Review of Retail, Distribution and Consumer Research, vol. 28, no. 3, pp. 259–276, Mar. 2018, doi: 10.1080/09593969.2018.1445657.
[4]. A. Quan-Haase and A. L. Young, "The Uses and Gratifications (U&G) Approach as a Lens for Studying Social Media Practice," The Handbook of Media and Mass Communication Theory, pp. 269–286, Mar. 2014, doi: 10.1002/9781118591178.ch15.
[5]. C. Xie, Y. Wang, and Y. Cheng, "Does Artificial Intelligence Satisfy You? A Meta-Analysis of User Gratification and User Satisfaction with AI-Powered Chatbots," International Journal of Human–Computer Interaction, vol. 40, no. 3, pp. 613–623, Sep. 2022, doi: 10.1080/10447318.2022.2121458.
[6]. A. H. Zadeh, M. Farhang, M. Zolfagharian, and C. F. Hofacker, "Predicting value cocreation behavior in social media via integrating uses and gratifications paradigm and theory of planned behavior," Journal of Research in Interactive Marketing, vol. 17, no. 2, pp. 195–214, Mar. 2022, doi: 10.1108/jrim-10-2020-0209.
[7]. M. U. Riaz, L. X. Guang, M. Zafar, F. Shahzad, M. Shahbaz, and M. Lateef, "Consumers' purchase intention and decision-making process through social networking sites: a social commerce construct," Behaviour & Information Technology, vol. 40, no. 1, pp. 99–115, Nov. 2020, doi: 10.1080/0144929x.2020.1846790.
[8]. G. Assefa and B. Frostell, "Social sustainability and social acceptance in technology assessment: A case study of energy technologies," Technology in Society, vol. 29, no. 1, pp. 63–78, Jan. 2007, doi: 10.1016/j.techsoc.2006.10.007.
[9]. L. Graf-Vlachy, K. Buhtz, and A. König, "Social influence in technology adoption: taking stock and moving forward," Management Review Quarterly, vol. 68, no. 1, pp. 37–76, Jan. 2018, doi: 10.1007/s11301-017-0133-3.
[10]. U. Holtgrewe, "New new technologies: the future and the present of work in information and communication technology," New Technology, Work and Employment, vol. 29, no. 1, pp. 9–24, Mar. 2014, doi: 10.1111/ntwe.12025.

[11]. C. Chiu, E. T. G. Wang, Y. Fang, and H. Huang, “Understanding customers’ repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk,” Information Systems Journal, vol. 24, no. 1, pp. 85–114, Jul. 2012, doi: 10.1111/j.1365-2575.2012.00407.x.
[12]. T. Hirunyawipada and A. K. Paswan, “Consumer innovativeness and perceived risk: implications for high technology product adoption,” Journal of Consumer Marketing, vol. 23, no. 4, pp. 182–198, Jun. 2006, doi: 10.1108/07363760610674310.
[13]. A. D. MIYAZAKI and A. FERNANDEZ, “Consumer Perceptions of Privacy and Security Risks for Online Shopping,” Journal of Consumer Affairs, vol. 35, no. 1, pp. 27–44, Jun. 2001, doi: 10.1111/j.1745-6606.2001.tb00101.x.
[14]. S.-S. Liaw and H.-M. Huang, “Perceived satisfaction, perceived usefulness and interactive learning environments as predictors to self-regulation in e-learning environments,” Computers & Education, vol. 60, no. 1, pp. 14–24, Jan. 2013, doi: 10.1016/j.compedu.2012.07.015.
[15]. A. Spahn, “Can Technology Make Us Happy?,” Well-Being in Contemporary Society, pp. 93–113, Nov. 2014, doi: 10.1007/978-3-319-06459-8_6.
[16]. Y. Cheng and H. Jiang, “How Do AI-driven Chatbots Impact User Experience? Examining Gratifications, Perceived Privacy Risk, Satisfaction, Loyalty, and Continued Use,” Journal of Broadcasting & Electronic Media, vol. 64, no. 4, pp. 592–614, Oct. 2020, doi: 10.1080/08838151.2020.1834296.
[17]. C.-L. Hsu and J. C.-C. Lin, “Understanding the user satisfaction and loyalty of customer service chatbots,” Journal of Retailing and Consumer Services, vol. 71, p. 103211, Mar. 2023, doi: 10.1016/j.jretconser.2022.103211.
[18]. Á. Dunne, M. Lawlor, and J. Rowley, “Young people’s use of online social networking sites – a uses and gratifications perspective,” Journal of Research in Interactive Marketing, vol. 4, no. 1, pp. 46–58, Mar. 2010, doi: 10.1108/17505931011033551.
[19]. A. Vohra and N. Bhardwaj, “Customer engagement in an e-commerce brand community,” Journal of Research in Interactive Marketing, vol. 13, no. 1, pp. 2–25, Mar. 2019, doi: 10.1108/jrim-01-2018-0003.
[20]. S. Kokolakis, “Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon,” Computers & Security, vol. 64, pp. 122–134, Jan. 2017, doi: 10.1016/j.cose.2015.07.002.

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ISSN: 3104-4115