Customer's Intention to Adopt AI Chatbots in E-Commerce Framework: Using Structural Equation Modeling

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***Abstract*—AI-powered chatbots (chatter robots) are increasingly used to enhance customer interactions and streamline support services in the e-commerce industry. They offer superior customer assistance on the Internet and alleviate the challenges faced by businesses in providing adequate customer support and engagement. However, since some popular mobile retail applications like Zalora have been known for using AI chatbots since 2017, little research has investigated customers' experiences and adoption. Thus, this research uses structural equation modeling (SEM) to create a framework that describes the influence of customer engagement, experiences, and attitudes when using e-commerce platforms with AI chatbots. The findings reveal that perceived usability and interactivity affect customers' cognitive and affective attitudes toward their intention to adopt AI chatbots in an e-commerce platform. At the same time, perceived intelligence impacts affective attitude, and anthropomorphism affects cognitive attitude. Consequently, cognitive and affective attitudes affect customers' intention to use AI chatbots in the platform. The results of the SEM showed that the framework for describing the factors that influence the Intention to adopt AI chatbots is generally statistically acceptable.**

Keywords—E-Commerce, AI Chatbots, Consumers' Intention, Framework, Structural Equation Modeling

I. Introduction

Chatbots have emerged as a powerful tool for businesses as they can perform critical functions such as operations, marketing, order processing, and cost-effective customer support [1]. Zalora is one of the most popular mobile retail applications in the Philippines, widely recognized for its features and brand [2]. The adoption of AI-driven smart image detection by Zalora serves to streamline search processes, empowering consumers to make well-informed purchase decisions. Research emphasizes the substantial impact of electronic service quality, exemplified by these innovative features, on consumer interest and the potential for repeat purchases [3].

While AI chatbots are an emergent technology in the e-commerce industry, some research studies on AI chatbots have only focused on their technological features, consumers' inferences of human characteristics to AI- chatbots, and their consequences on interaction [4]. More empirical research must be conducted in this context to understand better the specific factors that can influence customers' intention to use AI chatbots in e-commerce. The purpose of this study is to understand how factors that can affect their attitudes toward using an e-commerce platform can influence their intention to adopt AI chatbots. Specifically, the study will address the following research questions:

a) Do perceived usability, interactivity, perceived intelligence, and anthropomorphism affect customers' cognitive and affective attitudes when using AI chatbots in an e-commerce platform?

b) Do customers' cognitive and affective attitudes affect their intention to adopt AI chatbots in an e-commerce platform?

c) What framework can be proposed to describe the influence of customer engagement, experiences, and attitudes when using e-commerce platforms with AI chatbots based on a statistical model?

Theoretical Framework

Fred Davis developed the Technology Acceptance Model (TAM) to explain how people adopt new technology. TAM emphasizes that perceived ease of use and usefulness represent pivotal determinants of user behavioral intentions. Studies illuminate the adaptability of TAM principles to the distinctive features of AI chatbots in the e-commerce landscape [5]. Consequently, perceived intelligence, interactivity, and anthropomorphism emerge as crucial components within AI chatbots [6].

Fig. 1 illustrates the conceptual framework for this study. Perceived usability encompasses both ease of use and usefulness [7]. Perceived intelligence, interactivity, and anthropomorphism are incorporated into the use of AI chatbots, for they can enhance user experience and achieve specific goals. Cognitive and affective attitudes serve as intermediaries connecting users' perceptions to their ultimate intention to adopt AI chatbots in e-commerce [8]. By bridging the gap between perceived ease of use and perceived usefulness, these attitudes offer a holistic view of how users' cognitive evaluations and emotional responses influence their adoption intentions.

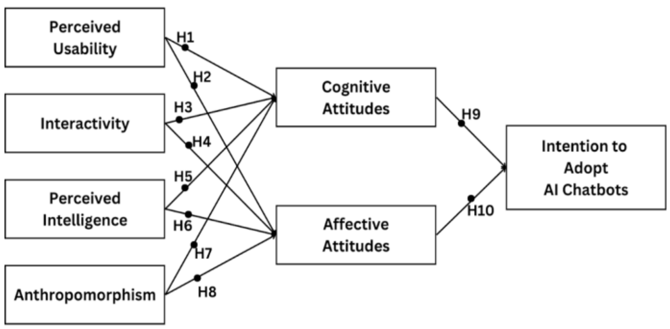

Fig. 1. Conceptual Framework

II. Review of Literature

A. Usability, Interactivity, Intelligence, and Anthropormism of AI Chatbots in E-Commerce

Chatbots are becoming more popular. One notable advantage of chatbots is their autonomy, eliminating human intervention [9]. In addition, chatbots can provide personalized recommendations and automated customer service assistance, ultimately contributing to elevated levels of customer satisfaction [10].

Perceived usability in AI chatbots significantly impacts how users think about (cognitive) and feel about (affective) the interaction. Designing chatbots with high usability leads to positive user experiences, encouraging adoption and trust. It is the same as with interactivity, anthropomorphism, and perceived intelligence [11]. To explore these assumptions, hypotheses H1 to H8 were formulated.

H1: There is no link between perceived usability and cognitive attitude toward AI chatbots.

H2: There is no link between perceived usability and affective attitude toward AI chatbots.

H3: There is no link between interactivity and cognitive attitude toward AI chatbots.

H4: There is no link between interactivity and affective attitude toward AI chatbots.

H5: There is no link between perceived intelligence and cognitive attitude toward AI chatbots.

H6: There is no link between perceived intelligence and affective attitude toward AI chatbots.

H7: There is no link between anthropomorphism and cognitive attitude toward AI chatbots.

H8: There is no link between anthropomorphism and affective attitude toward AI chatbots.

B. Cognitive and Affective Attitudes Towards Intention to Adopt AI Chatbots

To ensure successful adoption and integration of AI chatbots, it is essential to comprehend user attitudes towards them. The way users feel about the chatbots has a significant impact on their adoption. People who view them as easy to use, helpful, and reliable and have positive emotional responses like trust and satisfaction are likelier to use them. Comprehending these relationships is critical for designing user-friendly chatbots, enhancing the user experience, and driving successful adoption [12]. The subsequent hypotheses are put forth due to this occurrence:

H9: There is no link between cognitive attitude and adoption intention toward AI chatbots.

H10: There is no link between cognitive attitude and affective intention toward AI chatbots.

III. Methodology

A. Research Design

The study used a quantitative and correlational approach to investigate the relationship between customers' perceptions of usability, interactivity, intelligence, anthropomorphism, attitudes, and willingness to accept AI chatbots in an e-commerce platform. According to [13], using correlation in quantitative research is widely adopted in marketing research as it highlights the connections between variables and provides a deeper understanding of market and customer behavior. Hence, the researchers utilized the SEM approach to establish a framework that would explain the associations among the variables in the study.

B. Sampling

The researchers used purposive sampling, a non-probability technique for selecting respondents based on population characteristics and research objectives [14]. For this study, the criteria for selecting participants were individuals aged between 11 and 68 years old who currently reside in the Province of Laguna and have made a purchase through ZALORA in the last six months.

Determining an appropriate sample size is critical to ensure the study's reliability and accuracy without incurring unnecessary costs or complexities. The researchers determined that a sample size ranging between 200 to 300 purposively selected respondents would provide a suitable margin of error for the study.

C. Research Instrument

Data relevant to the study objectives and research questions were collected through a self-administered survey questionnaire using Google Forms. The questionnaire is divided into four parts. The first part is for obtaining the respondents' consent, while the second part is a screening process to ensure that only valid participants are included in the study. The third contains questions about the respondents' demographic profile. Lastly are the measures for seven (7) primary constructs. Perceived usability, as reflected in eleven items, was sourced from [15]; Interactivity items are adapted from: [16] and 17]; Perceived intelligence was gauged using thirteen items, originating from [18]; The scale of anthropomorphism, with twelve items, was adopted from [8]. Consumer affective and cognitive attitudes were measured with items drawn from adapted from [8].

Three experts in marketing and technology reviewed the initial instrument for pilot testing. Then, thirty-five respondents joined the pilot test. Using Cronbach's alpha, results showed that the items for each construct obtained a coefficient greater than 0.7, indicating the items consistently measure the same construct [19]. The final survey questionnaire comprised five (5) items for each construct, for a total of thirty-five (35).

D. *Statistical Treatment of Data*

To ensure the accuracy and reliability of the data, Warp PLS 6.0 software was used to assess the validity and reliability of the measuring model. This involved testing the relationships between a latent variable and its observed indicators using Cronbach's Alpha (CA) and Composite Reliability (CR). It's worth noting that an acceptable coefficient for CA and CR is deemed to be greater than or equal to 0.70. To establish a good measuring model, discriminant validity must be demonstrated. Discriminant validity can be determined by evaluating the AVE values, which must be at least 0.5. By meeting this criterion, the measuring model can be considered valid and acceptable [20].

TABLE I. CONVERGENT VALIDITY AND RELIABILITY

Constructs	A.V.E.	C.R.	C.A.
Perceived Usability (PU)	0.719	0.927	0.902
Interactivity (INT)	0.686	0.916	0.885
Perceived Intelligence (PI)	0.689	0.917	0.887
Anthropomorphism (ANT)	0.734	0.933	0.91
Cognitive Attitude (CA)	0.635	0.897	0.856
Affective Attitude (AA)	0.696	0.919	0.89
Adoption Intention (AI)	0.745	0.936	0.915

As shown in Table I, the proposed model's constructs are considered reliable since all values surpassed the required standards. Additionally, all latent variables met the necessary validity criteria, as indicated by the AVE coefficients and item loadings.

TABLE II. DISCRIMINANT VALIDITY USING FORNELL AND LARCKER

	PU	INT	PI	ANT	CA	AA	AI
PU	**0.848**						
INT	0.676	**0.828**					
PI	0.798	0.616	**0.83**				
ANT	0.502	0.516	0.646	**0.857**			
CA	-0.618	-0.468	-0.612	-0.469	**0.797**		
AA	0.663	0.834	0.715	0.652	-0.475	**0.834**	
AI	0.789	0.667	0.843	0.655	-0.591	0.811	**0.863**

Purchase Intention. Diagonal elements are the square root of the AVE of constructs, whereas the off-diagonal elements are the correlation between constructs.

The discriminant validity of an instrument is determined by the respondents' clarity and understanding of its items or measures. The correlation between variables is evaluated using the square roots of the AVE coefficient. To establish discriminant validity, the diagonal values in Table II must be higher than those in the same row to their left [21]. Table II presents the discriminant validity of the study measures. All constructs except INT and PI have square roots of AVE values greater than all the correlations. However, most correlations are less than the square root AVE of INT and PI. Thus, the discriminant validity of the two contracts is generally acceptable [22].

IV. RESULTS AND DISCUSSIONS

Unlike more straightforward techniques like correlation analysis, SEM allows the researchers to model and analyze multiple relationships between variables simultaneously. Understanding the interplay between customer engagement, experience, and AI capabilities is essential in obtaining a holistic view. This allows for a more nuanced understanding of each element's impact on the others [21].

A. *Influence of Customer Engagement, Experiences, and Attitudes when using E-commerce Platforms with AI Chatbots*

TABLE III. HYPOTHESIS TESTING FOR THE STRUCTURAL MODEL

Path	SE	Β	p	Ho
H1. PU → CA	0.20	-0.80	< .001	Reject
H2. PU → AA	0.17	-0.47	0.002	Reject
H3. INT → CA	0.10	0.21	0.019	Reject
H4. INT → AA	0.10	0.70	< .001	Reject
H5. PI → CA	0.17	0.04	0.834	Do not reject
H6. PI → AA	0.16	0.76	< .001	Reject
H7. ANT → CA	0.07	-0.25	0.008	Reject
H8. ANT → AA	0.05	0.04	0.519	Do not reject
H9. CA → AI	0.06	-0.28	< .001	Reject
H10. AA → AI	0.07	0.74	< .001	Reject

β – Path Coefficients SE – Standard Error

Table III shows the relationship or path between the study's constructs based on the SEM results. Out of ten (10) hypotheses, eight (8) showed significant results. The respondents' perceived usefulness (β = -0.80, $p < 0.001$), interactivity (β = 0.21, $p < 0.019$), and anthropomorphism (β = -0.25, $p < 0.008$) significantly impact their cognitive attitude when using e-platforms with AI chatbots. This means that respondents tend to be concerned about the potential threats of AI chatbots even if they perceive them to be helpful and have close-to-human-like interactions. On the other hand, users generally hold a favorable cognitive attitude toward AI chatbots with high interactivity.

Perceived usefulness (β = -0.47, $p < 0.002$), interactivity (β = 0.70, $p < 0.001$), and perceived intelligence (β = 0.76, $p < 0.001$) significantly impact their affective attitude. This statement implies that respondents exhibit a favorable emotional attitude toward utilizing AI chatbots, as they perceive them to possess high interactivity and offer accurate and dependable information regarding specific products and recommendations.

Lastly, the respondents' cognitive attitude about AI chatbots (β = -0.28, $p < 0.001$) significantly impacts their intention to use them when using e-commerce platforms. Despite apprehensions regarding personal security while engaging with AI chatbots, respondents seem to persist toward continued usage of the platform in the future. While their affective attitude (β = 0.74, $p < .001$) significantly and positively impacts their intention to use AI chatbots when using e-commerce. Customers are more likely to adopt AI chatbots if they find the experience satisfying.

B. Final Structural Model

One of the essential objectives of the study is to develop a model describing how perceived usability, interactivity, perceived intelligence, and anthropomorphism affect the adoption intention of customers as mediated by their cognitive and affective attitude. To test the significance of the paths in Fig. 1, SEM was run using Jamovi. The main exogenous (predictors) latent variables are PU, INT, PI, and ANT, while the main endogenous (dependent) latent variable is AI. On the other hand, CA and AA serve as the mediating latent variables between the main exogenous and endogenous variables. The insignificant paths in Table III were removed in the final structural model.

TABLE IV. MODEL FIT

Measures of Fit	Criteria	Obtained Values
Absolute Fit Indices		
Chi-square ($\chi 2$) GOF	p>0.05	1355 (<0.001)
Goodness-of-Fit Index (GFI)	≥0.90	0.957
Adjusted Goodness-of-Fit Index (AGFI)	≥0.90	0.948
Root Mean Square Error of Approximation (RMSEA)	0.05-0.08	0.070
Root Mean Square Residual (RMR)	<0.05	0.048
Incremental Fit Indices		
Normed Fit Index (NFI)	≥0.90	0.849
Comparative Fit Index (CFI)	>0.90	0.903
Tucker-Lewis Index (TLI)	Close to 1	0.894
Parsimony Fit Indices		
Parsimony Goodness-of-Fit Index (PGFI)	Close to 1	0.783
Parsimony Normed Fit Index (PNFI)	Close to 1	0.777

The final structural equation model was tested using the Chi-square goodness-of-fit ($\chi 2$ GOF) test, and the results are displayed in Table IV. The test produced a value of 1355 with a p-value less than 0.001. A significant chi-square value indicates a poor fit between the model and the data. However, it's crucial to remember that the chi-square test is influenced by sample size and model complexity [23].

The fit indices GFI (0.957) and AGFI (0.948) are sufficient, CFI (0.903) and TLI (0.894) are appropriate, and PGFI (0.783) and PNFI (0.777) are reasonable. The RMSEA is appropriate at 0.070, and RMR is acceptable at 0.048.

However, the NFI is below 0.90, although it is close to the threshold value. It's important to note that the three major measures of fit index were satisfied, indicating that the statistical model is generally valid and acceptable.

Fig. 2 shows a simple model that reflects the results of the structural equation modeling. This framework demonstrates how customers' intention to adopt AI chatbots in an E-Commerce platform is influenced by their cognitive and affective attitudes. These attitudes are, in turn, affected by perceived usability, interactivity, perceived intelligence, and anthropomorphism.

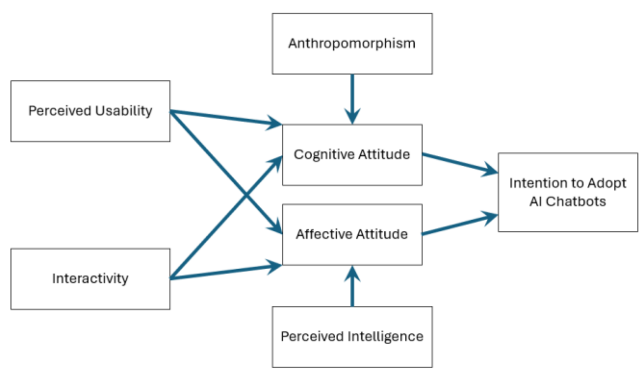

Fig. 2. Intention to Adopt AI Chatbots in E-Commerce Framework

V. CONCLUSION AND RECOMMENDATIONS

The study's final framework indicates that customers' perceived usability and interactivity significantly impact their cognitive and affective attitudes toward AI chatbots in an E-commerce setting. Additionally, anthropomorphism directly shapes cognitive attitudes, and perceived intelligence influences affective attitudes. These cognitive and affective attitudes are crucial in determining customers' intentions to use

AI chatbots in their future interactions with E-commerce platforms.

The current study has explored the relationship between user experiences and engagement with AI chatbots and their intention to use them. However, the study has not covered the direct effects of these experiences and engagement on users' behavioral intention to use AI chatbots. Hence, it is recommended that future researchers investigate the direct links between user experiences, engagement, and their intention to use AI chatbots. To achieve this, cognitive and affective attitudes can be added as primary mediators for the direct relationship between user experiences and engagement with their intention to use AI chatbots. Furthermore, it would be beneficial to widen the scope of the sample by including other E-commerce platforms like Shopee and Lazada. This will provide a more comprehensive understanding of how user experiences and engagement affect their intention to use AI chatbots across different platforms. Finally, demographic profiles like gender and income can be investigated as direct or mediating factors that influence users' behavioral intention to use AI chatbots. By exploring these factors, researchers can better understand how different demographic groups may perceive and use AI chatbots, which can help in designing more effective and user-friendly AI chatbots.

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