

The Influence of Perceived Usefulness and Perceived Risk on Actual Use Behavioral through Behavioral Intention on AI Chatbot E-commerce Marketplace Jabodetabek

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ABSTRACT

This research seeks to examine the correlation between users' perceptions of the AI chatbot's utility and risks and their actual use patterns on e-commerce platforms in the Jabodetabek region, as assessed using Behavioral intention. The quantitative survey methodology was used to survey 256 randomly chosen individuals. The information was gathered using an online questionnaire on a five-point Likert scale. The perceived danger did not significantly influence Behavioral intention, but perceived utility had a favourable and statistically meaningful effect. Behavioral Intention has a significant and positive influence on Actual Use Behavioral, but Perceived Usefulness lacks a direct impact on Actual Use Behavioral. The perceived risk positively and significantly affects actual use behaviour, contradicting the anticipated assumption. Moreover, Behavioral intention serves as a mediator between perceived benefit and actual Behavioral use, but it does not mediate the relationship between perceived risk and actual Behavioral usage.

INTRODUCTION

The public has higher expectations for AI chatbots' intelligence, speed, and contextual awareness due to the rise of Generative AI (ChatGPT and others) (Alhalabi et al., 2022; Aoki, 2020; Mohamad et al., 2026a). According to a DataReportal study carried out in 2025 (Simon Kemp, 2025), Indonesia is really one of the top 15 nations in terms of ChatGPT use globally. This trend shows that people in Indonesia are becoming used to using AI-based tools for research, suggestion-seeking, and decision-making assistance (Dwivedi et al., 2023; Lee et al., 2023; Mohamad et al., 2026b).

This trend has also encouraged the use of AI chatbots on e-commerce platforms to help with product information searches, provide ideas, and assist purchase activities. Research by (Jan et al., 2023) and (Cheng et al., 2022) indicates that e-commerce settings have made use of chatbots powered by artificial intelligence. However, there are still certain challenges that prevent their general use. One of these challenges concerns data security and privacy, as user interactions may involve conversation histories, shopping preferences, and account information (Liu et al., 2025; Pavlou, 2003; Sohn, 2024). Thus, the increasing implementation of AI Chatbots does not

necessarily lead to high levels of actual usage when users still consider the benefits and risks associated with the technology.

When considering whether or not to adopt a new technology, one of the most crucial considerations is the technology's perceived usefulness. Faster information retrieval, more successful searches, and decision-making assistance are all possible advantages of AI chatbots in online business. Perceived usefulness, together with trust and personal innovativeness, improves the intention to use AI chatbots, according to (Mohamad et al., 2026), while (Pham et al., 2025) revealed that perceived utility is a major element in raising Behavioral intention to use ChatGPT.

Conversely, perceivable risk may prevent people from using AI chatbots. Security, privacy, inaccurate information, and doubts about the technology's outcomes are all potential sources of perceived risk. Perceived danger reduces behavioral intention to use ChatGPT, according to (Lai et al., 2024). This means that consumers are less likely to embrace the technology when perceived risk is high. (Al-Hattami, 2025) shown that actual use behaviour in ChatGPT is adversely impacted by perceived danger, which is consistent with our findings. Thus, the perceived utility and perceived danger of AI chatbots are crucial aspects in understanding their adoption and utilisation.

Because it shows how prepared or eager people are to utilise a technology and might be a stepping stone to real use, Behavioral intention is another crucial component. Behavioral intention influences actual use behaviour positively, according to (Al-Hattami, 2025). That is, the probability of actually using an AI chatbot increases in direct proportion to the user's level of desire to do so. The evaluation of the effective use of AI technology relies on measuring actual usage, as Behavioral intention does not always correspond to real use behaviour (Wang et al., 2022).

Although research on AI Chatbots continues to develop, most previous studies have focused on behavioral intention and have paid relatively limited attention to whether such intention is actually translated into actual use behavioral. In addition, previous research has largely been conducted in the education sector, public services, or general technology contexts. Studies specifically examining AI Chatbots on e-commerce marketplaces in Indonesia remain relatively limited, despite the fact that their use is directly related to product searches, alternative evaluations, recommendations, and purchase decisions (Cheng et al., 2022; Jan et al., 2023).

Opportunities for future improvement of technology acceptance models have been highlighted in previous research as well. (Lai et al., 2024) showed that perceived risk works as a barrier to Behavioral intention, whereas (Pham et al., 2025) indicated that perceived usefulness plays an essential role in boosting Behavioral intention. There is a correlation between actual use behaviour and perceived danger and Behavioral intention, according to (Al-Hattami, 2025). This research fills a gap in our understanding of the understudied topic of artificial intelligence chatbots on online marketplaces by demonstrating the significance of

linking perceived advantages and disadvantages with functional utilisation via Behavioral intention.

This research tackles the existing information void by formulating an Extended Technology Acceptance Model (TAM). The concept posits that Behavioral intention serves as a mediator between perceived benefit and perceived danger, thereby influencing actual use behaviour. Extended TAM is an adaptation of the Technology Acceptance Model that incorporates technical specifics and the research context (Davis, 1989; Venkatesh et al., 2012). The goal is that by pursuing this approach, we could get deeper insights into how people perceive and engage with AI chatbots.

The extent to which clients believe an AI chatbot aids them in making a purchase is referred to as its perceived usefulness. The perceived advantages are essential for enhancing the propensity to use AI technology, as shown by many studies (Dahri et al., 2024; Mohamad et al., 2026b; Pham et al., 2025). A strong correlation exists between the perceived advantages and users' inclination to engage with AI Chatbots. From this account, one may propose the first hypothesis:

H1: Perceived Usefulness has a positive effect on Behavioral Intention in the use of AI Chatbots on e-commerce marketplaces.

Concerns about security, privacy, and information confusion are examples of the perceived risks that consumers may have while interacting with AI chatbots. The study by (Lai et al., 2024) shown that the intention to behave is negatively impacted by perceived risk. Users are less likely to want to utilise AI chatbots when they perceive a greater level of danger. This justification allows us to establish the following second hypothesis:

H2: Perceived Risk has a negative effect on Behavioral Intention in the use of AI Chatbots on e-commerce marketplaces.

Users' actual use of a technology is one manifestation of their Behavioral intention, which indicates their preparedness to utilise the technology. Behavioral intention influences actual use behaviour positively, according to (Al-Hattami, 2025). Consequently, consumers are more likely to make use of AI Chatbots if their Behavioral intention is strong. This justification allows us to express the third hypothesis in the following way:

H3: Behavioral Intention has a positive effect on Actual Use Behavioral in the use of AI Chatbots on e-commerce marketplaces.

Because people are more likely to use AI Chatbots for shopping if they believe they would profit from doing so, perceived usefulness is also likely to impact actual use. Perceived utility influences real system utilisation on Shopee e-commerce, according to (Agresdiant & Amelia, 2026). In light of this clarification, the following is the formulation of the fourth hypothesis:

H4: Perceived Usefulness has a positive effect on Actual Use Behavioral in the use of AI Chatbots on e-commerce marketplaces.

Concerns about privacy, security, and the veracity of the information they provide could make individuals reluctant to utilise AI chatbots, which means that perceived risk might hinder their actual adoption. As stated by (Al-Hattami, 2025), the impact of perceived threat on actual usage behaviour is negative. On the basis of this reasoning, here is the fifth possibility:

H5: Perceived Risk has a negative effect on Actual Use Behavioral in the use of AI Chatbots on e-commerce marketplaces.

Many believe that Behavioral intention acts as a moderator between the perceived usefulness and the actual use habit. When users see AI chatbots in a good light, they are more inclined to actually use them. (Al-Hattami, 2025) discovered that Behavioral intention affected actual use behaviour, while Pham et al. (2025) discovered that perceived usefulness influenced Behavioral intention, both of which support this relationship. With that out of the way, the sixth hypothesis may be stated as follows:

H6: Behavioral Intention mediates the effect of Perceived Usefulness on Actual Use Behavioral in the use of AI Chatbots on e-commerce marketplaces.

It is also claimed that Behavioral intention influences the impact of perceived risk on actual use behaviour. Individuals could defer using it until a lot later time if they are apprehensive about executing their intentions. (Lai et al., 2024) shown that perceived risk adversely influenced Behavioral intention, while (Al-Hattami, 2025) established a correlation between Behavioral intention and actual use conduct. The seventh hypothesis, derived from these data, is articulated as follows:

H7: Behavioral Intention mediates the effect of Perceived Risk on Actual Use Behavioral in the use of AI Chatbots on e-commerce marketplaces.

Given the foregoing, this study aims to investigate how online market AI chatbots are affected by perceived utility and perceived risk in relation to Behavioral intention. Not only will this study illuminate the real-world uses of AI, but it should also contribute to the advancement of AI chatbot research and development by illuminating ways in which user needs may be better recognised and fulfilled. The research model, derived from the theoretical review and assumptions, is shown in Figure 1. Interactions between the variables are shown.

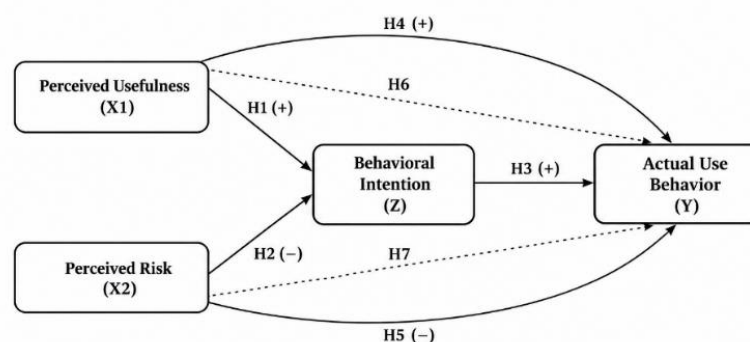


Figure 1. Research Model

RESEARCH METHOD

Using an explanatory survey methodology, this research takes a quantitative technique. Consumers in the Greater Jakarta (Jabodetabek) region who have used AI Chatbot services on e-commerce platforms are the subjects of this study, which aims to understand AI Chatbot usage on e-commerce marketplace platforms. Respondents' responses to an online questionnaire served as the main data source.

Participants in this research are online shoppers from the Jabodetabek region who have made use of AI Chatbot features on e-commerce sites including Blibli, Shopee, and Lazada. The needs of PLS-SEM analysis dictated the sample size since we do not know the precise number of users who fulfill the study criteria. Respondents were chosen using specified criteria pertinent to the study aims in a non-probability sample strategy known as purposive sampling. To be eligible, you needed to meet four requirements: (1) live in Jabodetabek; (2) be 17 or older; (3) have utilised an AI Chatbot on an e-commerce platform three times or more; and (4) have made an e-commerce transaction in the last six months.

A minimum of 180 participants was necessary for each metric, with the quantity of metrics used to ascertain the needed sample size (Hair et al., 2022). This research included 256 individuals who satisfied the inclusion criteria. Google Forms facilitated the execution of a digital survey. The survey gathered responses on a five-point Likert scale, with 1 indicating strong dissent and 5 indicating strong assent.

The poll included measures for Behavioral intention, perceived usefulness, risk, and actual Behavioral use. Individuals' perceptions of the product's utility, danger, Behavioral purpose, and actual use were evaluated using sets of five indications each. Indicators and operational definitions for all variables are shown in Table 1.

Table 1. Operational Definitions and Indicators of Variables

Variable	Operational Definitions	Indicators (Questionnaire Items)
Perceived Usefulness (X1)	The degree to which users believe that AI Chatbot provides benefits in their shopping activities.	PU1–PU5: helps complete activities more quickly; improves effectiveness in obtaining information; increases shopping productivity; facilitates decision-making; provides overall benefits in shopping activities.
Perceived Risk (X2)	Users' perceptions regarding the possibility of risks arising from the use of AI Chatbot.	PR1–PR4: risk to personal information; uncertainty of results; potential inaccuracy of information; risk related to trust in the service.
Behavioral Intention (Z)	Users' intention or willingness to use AI Chatbot in shopping activities.	BI1–BI4: intention to use; willingness to use AI Chatbot in the future; preference for using the chatbot; recommendation to others.
Actual Use Behavioral (Y)	Users' actual behavior in utilizing AI Chatbot on e-commerce platforms.	AUB1–AUB4: frequency of use; intensity of use; consistency of use; use of AI Chatbot during the purchasing process.

Partial Least Squares Structural Equation Modelling (PLS-SEM) and SmartPLS were used to analyse the data. This study used PLS-SEM because of its proficiency in analysing intricate relationships among latent variables and its capability to assess both direct and indirect effects

via a mediating variable. The study had two components: an assessment of the external (measurement) model and an assessment of the internal (structural) model.

Assessed the measurement model via reliability, discriminant validity, and convergent validity. Convergent validity was evaluated when the outer loadings and Average Variance Extracted (AVE) metrics reached a minimum of 0.70 and 0.50, respectively. Outcomes below 0.90 were considered satisfactory for assessing discriminant validity using the Heterotrait-Monotrait ratio (HTMT). Composite reliability and Cronbach's alpha were used to assess reliability; values beyond 0.70 were deemed satisfactory.

The structural model was evaluated by route coefficients, R-squared values, effect magnitude, and predictive significance. We used route coefficients to examine the intensity and orientation of associations across constructs, Q^2 to assess the significance of the predictions, R^2 to evaluate the explanatory power of the exogenous variables, and f^2 to determine the contribution of each construct. Employing the bootstrapping technique in SmartPLS, we analysed our hypotheses on the direct and indirect relationships, the mediating effect of Behavioral Intention, and their characteristics.

RESULT AND DISCUSSION

3.1. Respondent Characteristics

This research included 256 participants who satisfied the established screening requirements. The characteristics of the respondents are shown in Table 2.

Table 2. Profile and Screening Respondent

Screening and Characteristic	Category	Frequency	Percentage
Active e-commerce user	Yes	256	100.0
	No		
Interaction history	Yes	256	100.0
	No		
Gender	Male	137	53.5
	Female	119	46.5
Age	17-25 years old	117	45.7
	26-35 years old	96	37.5
	36-45 years old	26	10.2
	46-55 years old	12	4.7
	56-65 years old	5	2.0
Education level	Elementary School		
	Junior High School	3	1.2
	Senior High School/Equivalent	93	36.3
	Bachelor's Degree	146	57.0
	Master's Degree	13	5.1
	Doctoral Degree/Ph.D.	1	0.4
Domicile	Jakarta	81	31.6
	Bogor	20	7.8
	Depok	47	18.4
	Tangerang	61	23.8
	Bekasi	47	18.4
average expense	<= Rp. 200.000	31	12.1
	Rp. 200.001 s.d. Rp. 400.000	48	18.8
	Rp. 400.001 s.d. Rp. 600.000	47	18.4
	Rp. 600.001 s.d. Rp. 800.000	39	15.2
	Rp. 800.001 s.d. Rp. 1.000.000	49	19.1
	> Rp. 1.000.000	42	16.4

According to the findings of the screening, every single one of the 256 respondents was an active user of e-commerce platforms and had some kind of experience interacting with AI chatbots. Among the responders, 137 were men (53.5%) and 119 were women (46.5%). A total of 117 respondents (45.7% of the total) were in the age bracket of 17–25, with 96 respondents (37.5%) falling into the 26–35 age bracket. There were 26 responders (10.2%) in the 36–45 age bracket, 12 (4.7% of the total) in the 46–55 age bracket, and 5 (2.0% of the total) in the 56–65 age bracket.

Based on educational background, most respondents held a Bachelor's Degree, with 146 respondents (57.0%), followed by Senior High School or equivalent with 93 respondents (36.3%). Regarding domicile, respondents were distributed across Jakarta with 81 respondents (31.6%), Tangerang with 61 respondents (23.8%), Depok with 47 respondents (18.4%), Bekasi with 47 respondents (18.4%), and Bogor with 20 respondents (7.8%). In terms of average e-commerce expenditure, the largest proportion of respondents spent Rp800,001–Rp1,000,000 per month, totaling 49 respondents (19.1%), followed by Rp200,001–Rp400,000 with 48 respondents (18.8%) and Rp400,001–Rp600,000 with 47 respondents (18.4%). Overall, the respondent profile indicates that the study includes e-commerce users from various demographic and spending backgrounds in the Jabodetabek area.

3.2. Measurement Model Evaluation

By analyzing the measurement model, we were able to determine if the study's constructs were valid and reliable. The evaluation included tests for convergent validity, discriminant validity, and construct reliability.

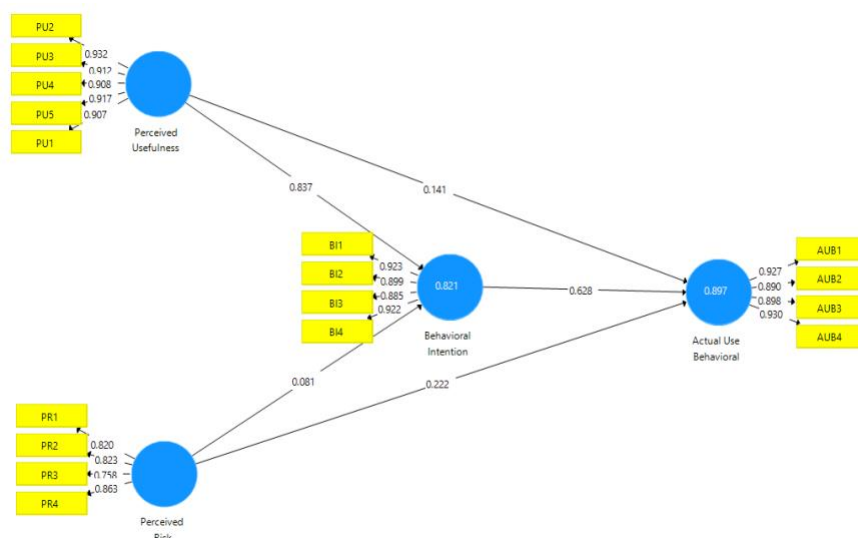


Figure 2. Model Evaluation

All of the indicator outer loadings were higher than the cutoff value of 0.70, according to the data. Outside loading values were between 0.758 and 0.932. Actual Use Behavioral had an AVE of 0.831, Behavioral Intention of 0.824, Perceived Risk of 0.667, and Perceived

Usefulness of 0.838. So, all the constructs had sufficient convergent validity as their AVE values were over the minimal threshold of 0.50.

Convergent Validity

Table 3. Outer Loading Value

Construct	Outer Loading	AVE
Actual Use Behavioral		0.831
AUB1	0.927	
AUB2	0.890	
AUB3	0.898	
AUB4	0.930	
Behavioral Intention		0.824
BI1	0.923	
BI2	0.899	
BI3	0.885	
BI4	0.922	
Perceived Risk		0.667
PR1	0.820	
PR2	0.823	
PR3	0.758	
PR4	0.863	
Perceived Usefulness		0.838
PU1	0.907	
PU2	0.932	
PU3	0.912	
PU4	0.908	
PU5	0.917	

All of the constructs' outer loading and AVE values are shown in Table 3. With values between 0.758 and 0.932, all of the indicators' outer loadings are more than 0.70. Outer loading values range from 0.758 for PR3 to 0.932 for PU2. Actual Use Behavioral has an AVE of 0.831, Behavioral Intention of 0.824, Perceived Risk of 0.667, and Perceived Usefulness of 0.838. The indicators appropriately reflect their respective conceptions and the measuring model meets the criterion for convergent validity because all outer loading values exceed 0.70 and all AVE values exceed 0.50.

Discriminant Validity

Table 4. Cross Loadings Result

	AUB	BI	PR	PU
AUB1	0.927	0.864	0.761	0.839
AUB2	0.890	0.854	0.755	0.804
AUB3	0.898	0.851	0.763	0.820
AUB4	0.930	0.824	0.771	0.807
BI1	0.857	0.923	0.725	0.827
BI2	0.831	0.899	0.728	0.813
BI3	0.820	0.885	0.684	0.791
BI4	0.870	0.922	0.727	0.853
PR1	0.679	0.624	0.820	0.702
PR2	0.701	0.683	0.823	0.762

PR3	0.583	0.578	0.758	0.603
PR4	0.757	0.686	0.863	0.692
PU1	0.841	0.848	0.804	0.932
PU2	0.826	0.827	0.762	0.912
PU3	0.795	0.785	0.783	0.908
PU4	0.822	0.841	0.775	0.917
PU5	0.820	0.838	0.751	0.907

There are cross-loading values for all indicators across all four constructions, as seen in the table above. Each indication is more heavily loaded on the construct with which it is most closely connected than on any of the other structures, according to the data. For instance, AUB1 ranks first on Actual Use Behavioral (with a loading of 0.927), BI1 on Behavioral Intention (with a loading of 0.923), PR4 on Perceived Risk (with a loading of 0.863), and PU2 on Perceived Usefulness (with a loading of 0.912). According to these findings, the indicators have a stronger association with their own constructions than with other constructs, lending credence to the idea of discriminant validity derived from cross-loadings.

Table 5. Fornell-Larcker Criterion Result

	AUB	BI	PR	PU
Actual Use Behavioral	0.911			
Behavioral Intention	0.931	0.908		
Perceived Risk	0.837	0.789	0.817	
Perceived Usefulness	0.897	0.905	0.847	0.915

The following table illustrates the Fornell-Larcker criterion used to evaluate construct-level discriminant validity. The diagonal values signify the square root of the AVE for each build. The figures are 0.911 for Actual Use Behaviour, 0.908 for Behavioral Intention, 0.817 for Perceived Risk, and 0.915 for Perceived Usefulness. This indicates that each construct exhibits more variance with its own indicators than with other constructs, since these values often surpass the correlations among the different constructs. Consequently, the Fornell-Larcker criteria substantiate discriminant validity.

Table 6. Heterotrait-Monotrait Ratio Result

	AUB	BI	PR	PU
Actual Use Behavioral				
Behavioral Intention	1.000			
Perceived Risk	0.946	0.895		

Perceived Usefulness	0.952	0.962	0.949
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Table 6 displays the HTMT outcomes. From 0.895 to 0.962, we find the values of the inter-construct connections. Relationships between Behavioral Intention and Perceived Usefulness and Actual Use Behavioral and Perceived Usefulness both have HTMT values that are higher than the generally used criterion of 0.90. Consequently, although the findings of cross-loading and Fornell-Larcker demonstrate discriminant validity, it is important to interpret with care the HTMT results since they indicate that many constructs have very high similarity.

Reliability

Table 7. Construct Reliability

Construct	Cronbach's Alpha	Composite Reliability
Actual Use Behavioral	0.932	0.951
Behavioral Intention	0.929	0.949
Perceived Risk	0.833	0.889
Perceived Usefulness	0.951	0.963

The results of the reliability tests for each concept are shown in the table. Composite dependability ranges from 0.889 to 0.963, while Cronbach's alpha spans from 0.833 to 0.951. All results above the minimum acceptable threshold of 0.70. The perceived usefulness is highlighted by a Cronbach's alpha of 0.951 and a composite reliability score of 0.963. These results indicate that the measuring techniques are dependable and that all concepts show significant internal coherence.

3.3. Structural Model Evaluation

Assessing collinearity, explanatory power, effect size, predictive relevance, and linkages among the constructs was the next step after evaluating the measurement model.

Variance Inflation Factor

Table 8. VIF Result

	VIF
Perceived Risk → Behavioral Intention	3.538
Perceived Usefulness → Behavioral Intention	3.538
Perceived Risk → Actual Use Behavioral	3.574
Perceived Usefulness → Actual Use Behavioral	7.441
Behavioral Intention → Actual Use Behavioral	5.577

The VIF values range from 3.538 to 7.441. The relationships Perceived Risk → Behavioral Intention and Perceived Usefulness → Behavioral Intention have the same VIF value of 3.538, while Perceived Risk → Actual Use Behavioral has a VIF of 3.574. However, Perceived Usefulness → Actual Use Behavioral has a VIF of 7.441, and Behavioral Intention → Actual Use Behavioral has a VIF of 5.577. These values indicate that potential collinearity requires attention, particularly among the predictors of Actual Use Behavioral.

Coefficient of Determination

Table 9. Coefficient of Determination (R^2)

	R Square	R Square Adjusted
Actual Use Behavioral	0.897	0.896
Behavioral Intention	0.821	0.819

Table 9 displays the endogenous constructs' coefficient of determination. Both the raw and adjusted R^2 values for Behavioral intention are 0.821 and 0.819, respectively. This means that with Perceived Usefulness alone, 82.1% of the variation in Behavioral Intention may be explained by other variables. The model's predictors account for 89.7 percent of the variation in Actual Use Behavioral, as shown by its R^2 value of 0.897 and modified R^2 of 0.896. Based on these findings, it is clear that the suggested model can adequately explain both endogenous variables.

Effect Size

Table 10. Effect Size (f^2)

	f^2
Perceived Risk $\rightarrow$ Actual Use Behavioral	0.134
Perceived Usefulness $\rightarrow$ Actual Use behavioral	0.026
Behavioral Intention $\rightarrow$ Actual Use behavioral	0.686
Perceived Risk $\rightarrow$ Behavioral Intention	0.010
Perceived Usefulness $\rightarrow$ Behavioral Intention	1.103

We can see how much of an effect each external construct had on the interior ones in Table above. Two significant relationships have been identified: one between perceived usefulness and Behavioral intention ($f^2 = 1.103$), and another between Behavioral intention and actual use ($f^2 = 0.686$). While Perceived Risk has a little effect on Behavioral Intention ($f^2 = 0.010$), it has a much larger effect on Actual Use Behavioral ($f^2 = 0.134$). Concurrently, the direct association between perceived usefulness and actual usage behaviour has an effect size of just 0.026. These findings demonstrate that, according to the structural model, Behavioral Intention plays a pivotal role in explaining Behavioral Intention, and that Perceived Usefulness is the most important component in Actual Use Behavioral.

3.4. Hypothesis Testing

The use of bootstrapping in SmartPLS was used for the purpose of hypothesis testing. Both Table 11 and Table 12 show the outcomes of the direct effects and indirect effects, respectively, with Behavioral Intention serving as a mediator in Table 12. A p-value less than 0.05 indicates a statistically significant association.

Table 11. Direct Effect Result

Hypothesis	Original Sampel	Sample Mean	Standar Deviation	T Statistics	P Value	Result
Behavioral Intention $\rightarrow$ Actual Use Behavioral	0.628	0.595	0.103	6.108	0.000	Supported

Perceived Risk → Actual Use Behavioral	0.222	0.222	0.037	6.068	0.000	Supported
Perceived Risk → Behavioral Intention	0.081	0.078	0.051	1.583	0.144	Not Supported
Perceived Usefulness → Actual Use Behavioral	0.141	0.174	0.114	1.233	0.218	Not Supported
Perceived Usefulness → Behavioral Intention	0.837	0.841	0.058	14.387	0.000	Supported

Table 12. Specific Indirect Effect Result

Hypothesis	Original Sampel	Sample Mean	Standar Deviation	T Statistics	P Value	Result
Perceived Risk → Behaviroal Intention → Acual Use Behavioral	0.051	0.049	0.036	1.416	0.157	Not Supported
Perceived Usefulness → Behaviroal Intention → Acual Use Behavioral	0.526	0.496	0.070	7.474	0.000	Supported

Table 11 indicates a positive and statistically significant relationship between Behavioral intention and actual Behavioral usage, shown by a path coefficient of 0.628, a t-statistic of 6.108, and a p-value of 0.000. The correlation between Perceived Usefulness and Behavioral Intention has a path coefficient of 0.837, a t-statistic of 14.387, and a p-value of 0.000. The t-statistic of 1.583 and a path coefficient of 0.081 indicate that perceived risk does not have a statistically significant influence on Behavioral intention ($p=0.144$). Actual Use Behavioral remains uninfluenced by Perceived Usefulness (t-statistic = 1.233, $p = 0.218$, and path coefficient = 0.141).

The findings indicate that Perceived Risk significantly and positively influences Actual Use Behavioral, shown by a path coefficient of 0.222, a t-statistic of 6.068, and a p-value of 0.000. This outcome is advantageous, contrary to the forecasts presented in H5. Consequently, we are unable to regard H5 as a legitimate hypothesis.

H1: Perceived Usefulness → Behavioral Intention

The results demonstrate positive and statistically significant impacts of Perceived Usefulness on Behavioral Intention ($\beta = 0.837$; $t = 14.387$; $p = 0.000$). This supports H1. This study indicates that individuals are more inclined to use AI chatbots in online marketplaces when they believe the technology would facilitate time and effort savings.

Our findings align with those of (Pham et al., 2025), who discovered that Perceived Usefulness significantly affects Behavioral Intention regarding ChatGPT. The users' assessment of the efficacy of AI chatbots influences their willingness to engage with these tools, a notion corroborated by the conclusions and research of Mohamad et al. (2026). Individuals are more inclined to use AI chatbots in an e-commerce setting if they see the technology as enabling authentic tasks such as information exploration and transaction finalization.

H2: Perceived Risk → Behavioral Intention

The impact of Perceived Risk on Behavioral Intention is positive but not statistically significant ($\beta = 0.081$; $t = 1.583$; $p = 0.144$). Thus, H2 cannot be accepted. Users' intentions to use AI Chatbots are not substantially impacted by perceived worries about privacy, security, information veracity, or ambiguity, according to the results.

Contrary to what (Lai et al., 2024) discovered, this study shows that Perceived Risk does not affect Behavioral Intention inside the ChatGPT scenario. Because of the technology's use and convenience, online shoppers may continue to plan to use AI chatbots while knowing about the hazards. The fact that Perceived Risk only has a little impact size on Behavioral Intention ($f^2 =$

0.010) lends credence to this theory, suggesting that it fails to provide much in the way of explanation.

H3: Behavioral Intention → Actual Use Behavioral

There is a strong and positive correlation between Behavioral intention and actual use behavior ($\beta = 0.628$; $t = 6.108$; $p = 0.000$). As a result, we may accept H3. The results show that people's actual use of AI chatbots is correlated with their intentions to utilize them.

(Al-Hattami, 2025) also discovered that Behavioral Intention favorably influences actual use behavior, therefore our results are in line with theirs. Behavioral Intention has the highest f^2 value toward Actual Use Behavioral at 0.686, which is supported by the impact size result and further supports this conclusion. So, according to the model, Behavioral Intention is the one that matters most for predicting how often people really use AI chatbots.

H4: Perceived Usefulness → Actual Use Behavioral

Perceived Usefulness has a positive but insignificant direct effect on Actual Use Behavioral ($\beta = 0.141$; $t = 1.233$; $p = 0.218$). Therefore, H4 is not supported. This result indicates that perceiving AI Chatbots as useful does not directly lead users to use the technology in actual shopping activities.

The finding suggests that perceived usefulness may influence actual usage through another mechanism, particularly Behavioral Intention. This interpretation is supported by the small effect size of Perceived Usefulness on Actual Use Behavioral ($f^2 = 0.026$), compared with its much stronger effect on Behavioral Intention ($f^2 = 1.103$). Thus, users may recognize the usefulness of an AI Chatbot but still require a strong intention to use it before the benefit is translated into actual behavior.

H5: Perceived Risk → Actual Use Behavioral

Perceived Risk has a positive and significant effect on Actual Use Behavioral ($\beta = 0.222$; $t = 6.068$; $p = 0.000$). However, H5 proposed a negative relationship. Therefore, H5 is not supported in the hypothesized direction.

The positive relationship indicates that respondents with higher perceptions of risk also tend to demonstrate higher actual AI Chatbot usage. This result is contrary to (Al-Hattami, 2025), who found a negative effect of Perceived Risk on actual usage behavior. A possible interpretation is that users who interact more actively with AI Chatbots may also become more aware of potential risks arising from their interactions. Thus, higher risk perception in this sample does not necessarily result in avoidance of the technology. Nevertheless, because the observed direction differs from the proposed hypothesis, this finding should be interpreted cautiously.

H6: Perceived Usefulness → Behavioral Intention → Actual Use Behavioral

Perceived usefulness has a positive and statistically significant indirect influence on actual use behavior via Behavioral intention ($\beta = 0.526$; $t = 7.474$; $p = 0.000$). That being the case, H6 is upheld.

As a mediator between perceived utility and actual behavioral usage, Behavioral intention is the focus of this research. Although it has little direct effect on Actual Use Behavioral, Perceived Usefulness significantly affects it indirectly via Behavioral Intention. This lends

credence to the idea that people are motivated to utilize AI chatbots because they believe the technology will be useful to them.

H7: Perceived Risk → Behavioral Intention → Actual Use Behavioral

The β -value of 0.051, t-value of 1.416, and p-value of 0.157 indicate that the indirect influence of Behavioral Intention on Actual Use Behavior is not statistically significant. H7 cannot be accepted as a result.

Perceived risk and actual behavioral use are not mediated by Behavioral intention, according to this study. The results are in line with the hypothesis that there is a weak direct correlation between PI and BI. The impact of Perceived Risk on Actual Use Behavioral is substantial, but it does not have a substantial influence via Behavioral Intention. This research concludes that users' intentions to utilizing the technology, do not mediate the effect of Perceived Risk on subsequent use.

Evaluasi Predict Model (PLS Predict)

Table 13. Prediction Result

	Q²_Predict	PLS- RMSE	LM- RMSE	PLS- MAE	LM- MAE
AUB1	0.704	0.666	0.671	0.562	0.556
AUB2	0.659	0.649	0.659	0.555	0.568
AUB3	0.683	0.603	0.607	0.503	0.499
AUB4	0.669	0.662	0.662	0.546	0.547
BI1	0.677	0.661	0.658	0.542	0.545
BI2	0.659	0.612	0.620	0.491	0.499
BI3	0.616	0.679	0.668	0.573	0.551
BI4	0.719	0.599	0.599	0.480	0.472

These are the endogenous constructions' PLS-Predict findings. The model accurately predicts the indicators of Behavioral Intention and Actual Use Behavioral, since all Q²_predict values are positive, ranging from 0.616 to 0.719. The results also demonstrate that the model can provide predictions for the indicators that have been observed. An extra way to evaluate the model's predictive capabilities is to compare PLS-RMSE and LM-RMSE, as well as PLS-MAE and LM-MAE.

For Actual Use Behavioral, the Q²_predict values range from 0.659 to 0.704, while the four Behavioral Intention indicators range from 0.616 to 0.719. The highest predictive relevance is observed for BI4 with a Q²_predict value of 0.719, whereas the lowest is observed for BI3 at 0.616. These results indicate that the model demonstrates meaningful predictive relevance across all indicators examined.

Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis (IPMA) was conducted to identify which constructs have the greatest impact (importance) on the target construct while simultaneously evaluating their current performance levels. In this study, IPMA was applied to two endogenous constructs: Actual Use Behavioral and Behavioral Intention.

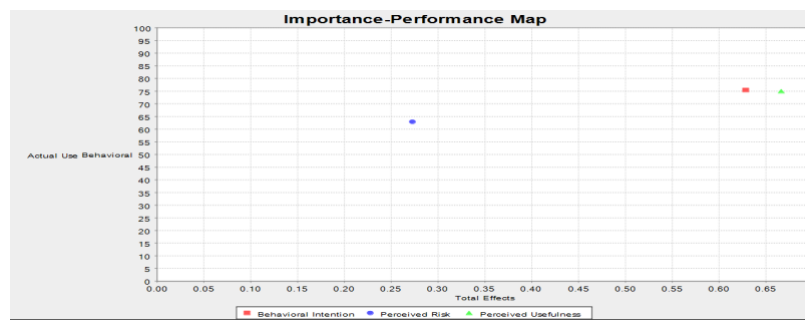


Figure 3. Importance-Performance Map Actual Use Behavioral

The Actual Use Behavioral Importance-Performance Map Analysis (IPMA) findings are shown in Figure 3. The vertical axis displays the significant value as measured by the total effect on Actual Use Behavioral, while the horizontal axis displays the performance score of each construct. The map illustrates the relationship between customers' actual actions while dealing with AI chatbots and their views of the bots' utility, danger, and Behavioral aim. Based on the results, Perceived Usefulness stands out with a performance score of 74.942 and a significant value of 0.654. This study adds to the growing body of information suggesting that improving Actual Use Behavioral relies heavily on how beneficial something is perceived to be. There are direct and indirect links between perceived usefulness and actual use, with the latter being particularly strong in regard to Behavioral intention. Despite the structural model's failure to detect a direct influence of perceived usefulness on actual usage behavior, the IPMA significance value which is derived from the overall effect provides evidence for this.

With a value of 0.647, Behavioral Intention is the second most important factor, and its performance score is 75,397, the highest. This construct is still one of the most powerful determinants of Actual Use Behavioral, suggesting that users already show a pretty high level of intention to use AI Chatbots. Therefore, maintaining users' behavioral intention is essential for sustaining actual AI Chatbot usage on e-commerce marketplaces. Meanwhile, Perceived Risk has the lowest importance (0.394) and the lowest performance score (62.891). This result suggests that perceived risk contributes less to Actual Use Behavioral compared with the other constructs. However, its relatively low performance indicates that aspects related to privacy, security, information accuracy, and transparency of AI Chatbots still provide opportunities for improvement in e-commerce marketplace services. Overall, Figure 3 suggests that increasing the perceived usefulness of AI Chatbots while maintaining users' behavioral intention offers the greatest potential for improving Actual Use Behavioral.

Table 14. IPMA Result (Actual Use Behavioral)

	Importance (Total Effect)	Performance
Behavioral Intention	0.647	75.397
Perceived Risk	0.394	62.891
Perceived Usefulness	0.654	74.942

Table 14 presents the Importance-Performance Map Analysis (IPMA) for Actual Use Behavioral. Perceived Usefulness has the highest total-effect importance value of 0.654, followed by Behavioral Intention at 0.647 and Perceived Risk at 0.394. In terms of performance, Behavioral Intention has the highest score at 75.397, followed by Perceived Usefulness at 74.942 and Perceived Risk at 62.891.

These results indicate that Perceived Usefulness is the most important construct in terms of total effect on Actual Use Behavioral, while Behavioral Intention demonstrates the highest performance level among the three constructs. Meanwhile, Perceived Risk has both lower

importance and lower performance compared with the other constructs. Therefore, improving the perceived usefulness of AI Chatbots and maintaining strong behavioral intention may be important considerations in increasing actual AI Chatbot usage on e-commerce marketplaces.

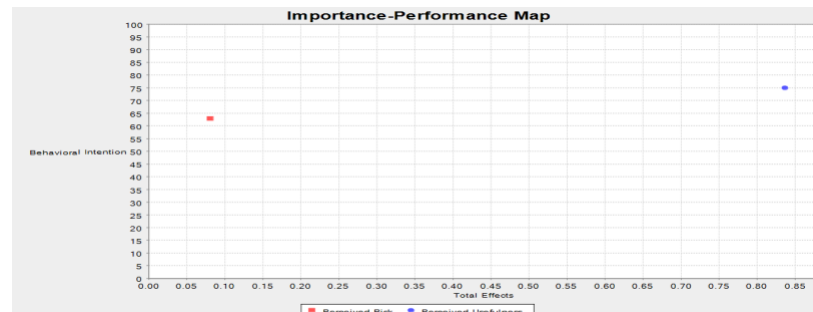


Figure 4. Importance-Performance Map Behavioral Intention

This analysis evaluates the relative importance and performance of Perceived Usefulness and Perceived Risk in explaining users' intention to use AI Chatbots on e-commerce marketplaces. The IPMA results show that Perceived Usefulness occupies the position with the highest importance and a high performance score. This finding indicates that users perceive AI Chatbots as beneficial for obtaining product information, receiving personalized recommendations, and supporting shopping decisions. As a result, improvements in perceived usefulness are expected to generate the greatest increase in Behavioral Intention.

In contrast, Perceived Risk demonstrates relatively lower importance and lower performance than Perceived Usefulness. This indicates that although respondents recognize potential risks associated with AI Chatbots, these concerns do not substantially influence their intention to use the technology. This interpretation is consistent with the hypothesis testing results, where Perceived Risk was found to have no significant effect on Behavioral Intention. Overall, Figure 4 indicates that strengthening users' perceived usefulness, such as improving chatbot response quality, recommendation relevance, and information efficiency is likely to be a more effective strategy for increasing Behavioral Intention than focusing solely on reducing perceived risk.

Table 15. IPMA Result (Behavioral Intention)

	Importance (Total Effect)	Performanc e
Perceived Risk	0.081	62.891
Perceived Usefulness	0.837	74.942

The performance numbers show the average latent variable scores on a 0–100 scale, while the importance values show the overall influence of each exogenous construct on Behavioral Intention. With a significance value of 0.837 and a performance score of 74.942, Perceived Usefulness stands out as the top performer according to the data. According to these results, the concept of perceived usefulness has the greatest impact on the explanation of Behavioral intention. What this means is that e-commerce marketplaces are more likely to see an increase in the desire to utilize AI Chatbots from consumers who find them helpful for finding product information, getting suggestions, and supporting purchasing choices. Users' Behavioral Intention may be most effectively increased by making AI Chatbots seem more beneficial.

On the other hand, Perceived Risk's performance score is lower (62.891) and its significance value is much lower (0.081). Based on these findings, it seems that perceived risk has a little role in explaining Behavioral intention in this research. Concerns about privacy, security,

information accuracy, and ambiguity are not key factors in respondents' desire to use AI chatbots, even though they are aware of these dangers. This reading is in line with the findings of the hypothesis testing, which demonstrate that Behavioral Intention is unaffected by Perceived Risk. Overall, the IPMA results indicate that Perceived Usefulness should be prioritized when developing strategies to strengthen users' Behavioral Intention toward AI Chatbots in e-commerce marketplaces. Meanwhile, improvements in Perceived Risk, particularly regarding privacy protection, transparency, and information reliability, may enhance users' perceptions of the technology even though its overall contribution to Behavioral Intention is relatively small.

CONCLUSION

The study's overarching goal was to learn how customers' views on the AI chatbot's use and potential danger influenced their real actions on Jabodetabek's e-commerce sites. An examination of 256 participants using PLS-SEM indicates that Perceived Usefulness has a positive and statistically significant influence on Behavioral Intention. This suggests that customers are more predisposed to engage with AI chatbots when they perceive more advantages. An individual's assessment of danger does not influence their desire to act.

The structural model demonstrates that Behavioral Intention has a strong and favorable impact on Actual Use Behavioral, establishing it as the primary predictor of AI chatbot use. The influence of Perceived Usefulness on Actual Usage Behavior is minimal, indicating that it mostly impacts actual usage via Behavioral Intention. This is also corroborated by the evidence that Behavioral Intention modulates the connection between Perceived Usefulness and Actual Use Behavior.

The perceived threat significantly influences actual use behavior positively; the prediction of a negative correlation proposed by the research was incorrect. This refutes the proposed adverse correlation. Moreover, there is no substantial indirect effect of Perceived Risk on Actual Use Behavior via Behavioral Intention, and Behavioral Intention does not serve as a mediator in the association between Perceived Risk and Actual Use Behavior.

In conclusion, the findings indicate that Behavioral Intention is essential for transforming users' anticipations about AI Chatbots into their genuine interaction with the technology. The results support the notion of broadening the Technology Acceptance Model to include Perceived Risk in the context of using artificial intelligence chatbots in online marketplaces. To foster genuine sustainable use among consumers, e-commerce companies had to emphasize on the utility, precision, and dependability of AI chatbots, all while maintaining data security and transparency.

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