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The Influence of Artificial Intelligence on Readiness and Acceptance of Technology in E-Commerce

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ABSTRACT

The use of artificial intelligence in e-commerce makes it easier for users to do online shopping. However, user data collection carried out by artificial intelligence in e-commerce can be misused. This is a shift in intention to adopt artificial intelligence in e-commerce. This study aims to identify the factors that impact the adoption of artificial intelligence in the field of e-commerce. The technology readiness model and the technology acceptance model are both utilized in this study. Data was collected from 283 students who have done shopping in e-commerce. The data collected will then be analyzed using SEM-PLS. The findings suggest that optimism, innovativeness, and discomfort have a role in shaping the acceptability of artificial intelligence in e-commerce, through the perceived ease of use and perceived usefulness. However, research findings suggest that there is no correlation between insecurity and the perceived ease of use and usefulness. The findings suggest that the way users view the ease of use, and the utility of artificial intelligence technology directly influences their acceptance of it in e-commerce, which is then through in their intention to use it. The result of this study can be used by online businesses to apply TAM and technology readiness models to maximize the use of AI in e-commerce.

Keywords: *Artificial Intelligence, E-Commerce, Online Shopping*

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INTRODUCTION

In this digital era, technological developments have changed the business paradigm, especially in the e-commerce sector. One of the main factors participating in this change is the presence of artificial intelligence (AI) (C. Wang et al., 2023). AI not only impacts technological aspects, but also affects consumer behavior in online shopping (Bilal et al., 2024). The growing utilization of artificial intelligence in comprehending consumer buying patterns has propelled the advancement of recommendation systems on e-commerce platforms, which play a role as factor in the decision-making process of purchase (Cabrera-Sánchez et al., 2020). Therefore, e-commerce can direct marketing efforts more effectively by recommending convenient products and making product offers to understand consumer behavior more accurately (Beyari & Garamoun, 2022). Artificial intelligence in the business world can be used to obtain decisions about marketing strategies derived from the results of e-commerce data analysis (Verma et al., 2021).

Artificial Intelligence can create engaging and interactive consumer experiences, increasing their willingness to share personal information (Kronemann et al., 2023). Artificial Intelligence systems often use large amounts of data, if the data is not properly secured, it is vulnerable to breaches and can lead to unauthorized access and misuse of sensitive data (Al-Khassawneh, 2022). Concerns regarding privacy violations including violations of rules for collecting and processing personal data, use of personal data, and privacy violations are still issues of Artificial Intelligence in e-commerce (Kolodin et al., 2020). Consequently, this could result in customers experiencing discomfort and concern, which could result in a change in intention due to the technology's lack of utility. (Michael Musyaffi et al., 2022).

According to Statista Market Insights data, the number of e-commerce consumers in Indonesia has been consistently increasing every year since 2018 (Mustajab, 2023). The prevalence of online buying has surged in Indonesia with the implementation of COVID-19 limitations. Based on data from Bank Indonesia, e-commerce transactions in 2018 recorded the number of consumers at Rp. 106 trillion while in 2020, it was recorded at Rp. 266 trillion (Pancawati, 2023). There was an increase of almost three times from the previous year. But behind the convenience offered, shopping online also has risks that need to be considered: fraud by sellers such as sending fake goods or goods not delivered, unsafe payment methods, and customer data leaks. In March 2020, Tokopedia, an e-commerce platform in Indonesia, was subjected to a cyber-attack resulting in the unauthorized disclosure and sale of 91 million consumer accounts and 7 million vendor accounts on the dark web (CNN Indonesia, 2020).

The study aims to discover the factors that influence the adoption of Artificial Intelligence technology in Indonesia. (C. Wang et al., 2023) suggested conducting further research from other countries to generalize findings; AI is an integral part of e-commerce. Due to changes in consumer behavior after the COVID-19 pandemic, AI adoption is increasing daily (Luo et al., 2023). E-commerce needs to find out the factors that can serve businesses and customers well (Svobodová & Rajchlová, 2020). AI is a relatively new technology, and its usefulness for e-commerce businesses is only part of its features (ERDOĞAN, 2023). Factors influencing AI acceptance in different contexts have been reported in the literature. However, much work remains to be done to assess how e-commerce consumers react to AI and how artificial intelligence can improve e-commerce efficiency. Studies on the enablers and barriers to adopting AI technologies in e-commerce are also limited.

This study utilizes a framework consisting of seven items derived from two adoption theories to examine the determinants of AI technology adoption: the Technology Readiness model (TR), which includes optimism, innovativeness, insecurity, and discomfort (Parasuraman, 2000); and Technology Acceptance Model (TAM) theory (Davis, 1986), which includes perceived usefulness, intention to use, and perceived ease of use.

Technology Acceptance Model

The expand technologies acceptance model is the theory that bulk frequently utilized to evaluate the acceptance of artificial intelligence technologies (Kelly et al., 2023). The technology acceptance model, formulated by (Davis, 1986), posits that a user's general attitude toward adopting an information technology system directly impacts their intention to accept and utilize the technology. The Technology Acceptance Model (TAM) includes several components, including perceived usefulness, perceived ease of use, intention to use, and technology adoption (C. Wang et al., 2023). The advantage of AI in e-commerce is that it makes it easier for consumers to shop online in less time. The quality of AI in e-commerce allows consumers to continue to use it in their daily lives.

Technology Readiness Model

The technological readiness model is a framework utilized to evaluate an individual's propensity to embrace and employ new technology (Parasuraman, 2000). The technology readiness model has supporting and inhibiting factors to determine user preferences in using new technology (Damerji & Salimi, 2021). Users can assess technology readiness with supporting factors such as optimism and innovation and inhibiting factors such as insecurity and discomfort (Rahardja et al., 2023).

Hypothesis Development

Optimism signifies that users are at the vanguard of maximizing the capabilities and features of technology. More optimistic users tend to find new technology easily, so they will more easily master new technology. prior research demonstrates that show there is a positive correlation between optimism and perceived ease of use when it comes implementation of AI technology in retail establishments (Pillai et al., 2020). Then, more than seventy percent according to several surveys conducted in Asian countries consumers use goods from several brands only because they believe in these brands (Castro & Chambers, 2019). Thus, the proposed hypothesis is as follows:

H1: Optimism positively influences perceived ease of use

H2: Optimism positively influences perceived usefulness

Innovativeness refers to the process of creating new technology or enhancing old technology to address changing requirements (Rahmania et al., 2023). With improvements or developments, users will feel they get the convenience and usefulness of using a technology, so they tend to use it. Innovativeness is proven to positively influence perceived ease of use on consumer shopping intentions in retail stores that adopt artificial intelligence (Pillai et al., 2020). Additional studies on the integration of artificial intelligence in recruitment systems have found a positive association between innovativeness and the perceived usefulness of such technology (Lee et al., 2021). Hence, the hypothesis can be stated as follows:

H3: Innovativeness positively influences perceived ease of use

H4: Innovativeness positively influences perceived usefulness

Insecurity reflects a person's doubts about technology and concerns about whether the technology can function properly (Mahmood et al., 2023). This doubt can be a barrier for someone to accept new technology (Fikri et al., 2022). The higher this factor, the more negative a person's view of technology which can hinder the receiving of new technological adoption (Zaman et al., 2023). Prior studies have established that insecurity significantly impacts the perceived ease of use and usefulness of digital banking adoption research (Michael Musyaffi et al., 2022). Therefore, the fifth and sixth research hypotheses are as follows:

H5: insecurity positively influences perceived ease of use

H6: insecurity positively influences perceived usefulness

Discomfort can engender unfavorable opinions of technology and diminish a person's willingness to accept and employ novel technology (Blut & Wang, 2020). Someone who experiences discomfort in the form of anxiety and fear tends to be less enthusiastic and responsive in the adoption of new technology (Donmez-Turan & Oren, 2021). According to prior research, tell that discomfort has a positive impact on perceived ease of use on student readiness to adopt e-learning (Kampa, 2023). Furthermore, a separate study has also discovered a direct correlation between feelings of discomfort and the perceived usefulness of trust and knowledge in the context of metaverse technology (Jeong & Kim, 2023). So, the next hypothesis is as follows:

H7: Discomfort positively influences perceived ease of use

H8: Discomfort positively influences perceived usefulness

The credence that the technology employed can deliver advantages to its user is referred to as its perceived usefulness (Khoa, 2021). Users will not prioritize the use of a technology that does not offer any tangible advantages in return. One is more inclined to utilize a technology that is straightforward to operate (Aiolfi, 2023). Likewise, with the features that can be used by consumers in e-commerce that have adopted artificial intelligence technology, the more features that help them in doing online shopping, the more the use of artificial intelligence technology in e-commerce will increase (Nicolescu & Tudorache, 2022). Continuous technology adoption is more likely to occur after individuals experience the convenience and benefits of technology through their own usage (Uren & Edwards, 2023). prior studies have established that intention to use constitutes a significant determining in the process of technology adoption (C. Wang et al., 2023). The hypothesis is therefore as follows:

H9: Perceived ease of use positively influences the intention to use AI technology in e-commerce.
H10: Perceived usefulness positively influences the intention to use AI technology in e-commerce
H11: Intention to use AI technology in e-commerce positively influences the adoption of AI technology in e-commerce

From the previous description, the constructs are interrelated and form a series of hypotheses. These hypotheses can be combined to form a research model. figure 1 below shows the relationship between the hypotheses that form the research model.

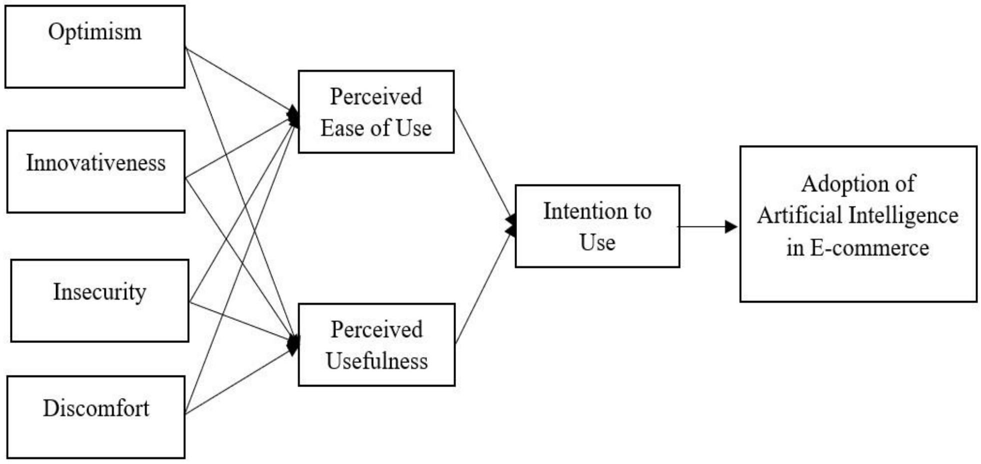

Figure 1. Research Model

RESEARCH METHOD

By employing a quantitative method, this examination identifies the factors that affect the implementation of artificial intelligence technology in e-commerce in Indonesia. The Smart PLS 4.0 software enabled the SEM-PLS method for the analysis of primary data. We acquired the main data for this research by distributing online questionnaires to participants living in the cities of Cirebon, Indramayu, Majalengka, and Kuningan. The population of this study is students who have experience making transactions through e-commerce platforms including Shopee, Lazada, Tokopedia, and Blibli. The research sample amounted to 283 respondents selected using the snowball sampling technique. The reason for choosing this approach is the challenge of accessing or identifying the target population and the scarcity of information about it (Leighton et al., 2021). With the criteria (1) students who are studying at universities in the Cirebon, Indramayu, Majalengka, and Kuningan regions, (2) have made purchases in e-commerce.

Data collection stage through the questionnaire in several steps. Firstly, participators were queried to provide information on their demographic characteristics such as gender, age, and the degree of online shopping just to mention a few. We must highlight that full names and residence details were not included in the research database because of security reasons. Consequently, participants needed to rate different statements with a 5-point Likert scale, in which 1 means strongly disagree and 5 means strongly agree. Data collection is aimed at collecting numerical data which will then be subjected to analysis and will be the basis on which the research hypothesis is tested. At all points of the study, the privacy and the anonymity of the respondents were preserved.

The data gathered in this research were examined utilizing SEM-PLS. The reason for choosing this method is because PLS can be used to test the research model built by researchers, starting with inner and outer model analysis, as well as model fit, and then evaluating the results based on the hypothesis that has been built. (Ghozali, 2021).

RESULT AND DISCUSSION

The demographics of the respondents who participated in this research appear in Table 1 below. Most of the respondents were female, accounting for 71.7% of the respondents, while only 28.3% were male. On the other hand, most respondents were between 20 and 21 years of age, accounting for 42% of the respondents. Section 3 tabulates the respondents' level of online shopping experience, with 56.2% of respondents having between 2 and 5 years of online shopping experience.

Table 1. Demographic profile of respondents

Variable	N (%)
Gender	
Male	80 (28,3%)
Female	203 (71,7%)
Age	
18-19	49 (17,3%)
20-21	119 (42%)
22-23	86 (30,4%)
>23	29 (10,2%)
Online Shopping Experience Levels	
<2	60 (21,2%)
2 -5	159 (56,2%)
>5	64 (22,6%)

Source: Data Analysis Result

Measurement Model

The model measurement consists of three main components, namely the first to analyze internal consistency, assess construct validity, and determine discriminant validity. In assessing internal consistency, the Composite Reliability value is the recommended measure. Table 2 shows that the INSC construct had a high composite reliability value of 0.898, while the DSCM construct had a low composite reliability value of 0.830 in the measurement model. However, despite these differences, can be concluded that the constructs in this study generally conform to the recommended value of 0.7 for composite reliability (Hair et al., 2019).

Table 1. Cross Loading, Cronbach’s Alpha, Composite Reliability, and AVE

Construct	Items	Loadings	Cronbach's Alpha	Composite Reliability	AVE
Optimism	OPTM1	0.768	0.711	0.838	0.634
	OPTM2	0.808			
	OPTM3	0.812			
Innovativeness	INNV1	0.749	0.709	0.835	0.629
	INNV2	0.801			
	INNV3	0.826			
Insecurity	INSC1	0.845	0.792	0.898	0.816
	INSC2	0.958			
Discomfort	DSCM2	0.757	0.693	0.830	0.619
	DSCM3	0.774			
	DSCM4	0.829			
Perceived Ease of Use	PEOU1	0.803	0.816	0.872	0.577
	PEOU2	0.715			
	PEOU3	0.747			
	PEOU4	0.757			
	PEOU5	0.774			
Perceived Usefulness	PU1	0.744	0.797	0.868	0.623
	PU2	0.826			
	PU3	0.818			
	PU4	0.764			
Intention to Use	ITU1	0.771	0.723	0.844	0.644
	ITU2	0.831			
	ITU3	0.803			
Adoption of AI in E-commerce	AAIE1	0.729	0.734	0.847	0.650
	AAIE2	0.842			
	AAIE3	0.842			

Source: Data Analysis Result, 2024

In the next step, the study analyzed the construct validity by looking at the outer loading value. INSC construct showed a high outer loading value of 0.958 and PEOU construct showed a low outer loading value of 0.715. However, all outer loading values in this study met the recommended criteria of greater than 0.7 (Hair et al., 2019). In addition, construct validity be judged using the Average Variance Explained (AVE) value. If the AVE value for a construct is higher than 0.5, can be concluded that the construct has well construct validity. According to the analysis results, AVE values for all constructs considered in this study exceed 0.5, indicating sufficient construct validity.

The Heterotrait-Monotrait Ratio (HTMT) values reported in Table 3 for the constructs in this study are less than 0.9. HTMT values below 0.9 indicate that the constructs in this study are indeed heterogeneous and can be distinguished from each other (Hair et al., 2019). Thus, can be concluded that well-discriminated validity can be established.

Table 2. Heterotrait-Monotrait Ratio Value

	AAIE	DSCM	INNV	INSC	ITU	OPTM	PEOU	PU
AAIE								
DSCM	0.531							
INNV	0.689	0.707						
INSC	0.292	0.425	0.378					
ITU	0.873	0.525	0.625	0.219				
OPTM	0.791	0.521	0.745	0.172	0.719			
PEOU	0.823	0.631	0.763	0.266	0.702	0.766		
PU	0.746	0.659	0.757	0.130	0.677	0.769	0.885	

Source: Data Analysis Result, 2024

Structural Model

Structural modeling is used to evaluate the relationship between constructs in the research model. The first is to test for multicollinearity problems. Based on Table 4, all constructs in this research model have VIF values that are less than 10. VIF values that are below 10 indicate nothingness of multicollinearity in a structural model. (Hair et al., 2019).

Table 3. Multicollinearity

	AAIE	ITU	PEOU	PU
AAIE				
DSCM			1.417	1.417
INNV			1.684	1.684
INSC			1.145	1.145
ITU	1.000			
OPTM			1.441	1.441
PEOU		2.049		
PU		2.049		

Source: Data Analysis Result, 2024

Second is the R-squared analysis: the R-squared values can be classified into three levels: large (0.75), moderate (0.50), and weak (0.25) (Hair et al., 2019). According to Table 5, all R-squared values in this study model belong to the weak category. This result indicates that the external factors OPTM, INNV, INSC, and DSCM explain only 48.1% of the variation in PU (perceived usefulness). In other words, the variation in PU that these external factors cannot explain amounts to 51.9%.

Table 4. R Square

	R-square	R-square adjusted	Criteria
AAIE	0.425	0.423	Weak
ITU	0.326	0.321	Weak
PEOU	0.485	0.478	Weak
PU	0.481	0.474	Weak

Source: Data Analysis Result, 2024

Next is the effect size test. There are three categories used to interpret the f-square value: Small (0.02), Medium (0.15), and Large (0.35) (Hair et al., 2019). According to Table 6, the highest f-square value 0.738 was found in the ITU structure, which is categorized as a large effect. On the other hand, the lowest f-square value of 0.005 was found for the relationship between the INSC structure and PEOU, which can be categorized as a small effect.

Table 5. Effect Size

	AAIE	ITU	PEOU	PU
AAIE				
DSCM			0.043	0.082
INNV			0.108	0.102
INSC			0.005	0.011
ITU	0.738			
OPTM			0.167	0.154
PEOU		0.090		
PU		0.050		

Source: Data Analysis Result, 2024

The Q^2 value is then analyzed. If the Q^2 worth of the endogenous structure is higher than 0, can concluded that the model has good predictive power for this structure. On the contrary, when the Q^2 value is lower than 0, the model has insufficient predictive power (Hair et al., 2019). According to Table 7, the PEOU structure has the highest Q^2 value of 0.467. Meanwhile, other endogenous constructs in this study also have Q^2 values higher than 0. This finding indicating that structural model tested has an adequate ability to predict the original observed values of the endogenous variables.

Table 6. Q Square

	Q^2	RMSE	MAE
AAIE	0.253	0.873	0.693
ITU	0.289	0.855	0.661
PEOU	0.467	0.741	0.56
PU	0.463	0.743	0.564

Source: Data Analysis Result, 2024

Hypothesis Testing

Hypothesis testing involves comparing the obtained probability value (p-value) with the predetermined significance level set at 0.05. If the p-value obtained is lower than has been determined previously significance level of 0.05, the hypothesis can be accepted. Conversely, if the p-value a higher than the significance level of 0.05, the hypothesis is rejected (Hair et al., 2019). The test results in Table 8 indicate that of the 11 hypotheses presented in this study, two hypotheses were rejected, and nine hypotheses were accepted.

Table 7. Hypotheses Testing

Hypothesis	Original sample	p values	Description

DSCM -> PEOU	0.178	0.002	**Accepted**
DSCM -> PU	0.245	0.000	**Accepted**
INNV -> PEOU	0.306	0.000	**Accepted**
INNV -> PU	0.298	0.000	**Accepted**
INSC -> PEOU	0.053	0.231	**Rejected**
INSC -> PU	-0.079	0.125	**Rejected**
ITU -> AAIE	0.652	0.000	**Accepted**
OPTM -> PEOU	0.352	0.000	**Accepted**
OPTM -> PU	0.340	0.000	**Accepted**
PEOU -> ITU	0.352	0.000	**Accepted**
PU -> ITU	0.263	0.002	**Accepted**

Source: Data Analysis Result, 2024

Our results show that intention to use is an important influencing factor in the adoption of AI in e-commerce, which along with the findings of (Michael Musyaffi et al., 2022), who discovered that intention to use plays an important in the acceptance model. The vantage of using AI in e-commerce is it makes it easier for users to shop online. Artificial intelligence in e-commerce can carry out all seller functions, such as offering products that match consumer interests, advertising, replying to questions or complaints from consumers, searching for products according to consumer orders, and being able to do various payment options such as cash and non-cash. Consumers can be more inclined to utilize artificial intelligence capabilities in e-commerce due to its convenience. Previous studies have demonstrated that perceived usefulness and perceived ease of use have a positive influence on technology adoption (Damerji & Salimi, 2021; Sudaryanto et al., 2023; C. Wang et al., 2023). The more consumer interest in technology will affect the intensity.

Perceived ease of use and perceived usefulness affect intention to use. This is the same as with previous researchers (Michael Musyaffi et al., 2022; Rahayu et al., 2022) that concluded the intention to use a technology is the most important factor in technology adoption. The study's findings also demonstrate how artificial intelligence functions in e-commerce, encouraging consumers to continue utilizing these features. Several features of artificial intelligence in e-commerce help consumers quickly meet their needs, such as quick searches using photos or voices, which will immediately bring up products according to the images in the photo or spoken voices.

Another finding is optimism has a positive impact on perceived usefulness and perceived ease of use, which is consistent with (Pillai et al., 2020) findings of a positive relationship between optimism with perceived usefulness, and perceived ease of use. Trust in products or services is a technology and e-commerce component (Liu & Yang, 2021). Trust strongly influences consumer behavior, especially in electronic payments and online purchases (Haenlein et al., 2020). The presence of new technologies that provoke positive reactions is due to the perception of their usefulness and ease of use in various functions that effectively increase productivity. If consumers perceive that new products or technologies offer additional benefits, this will increase the adoption and use of technology, especially AI technology, in e-commerce.

The innovativeness construct significantly influences both perceived usefulness and perceived ease of use, different from previous research (Michael Musyaffi et al., 2022) that found no significant impact on perceived usefulness and ease of use. This study aligns with research findings of (Y. Wang et al., 2020) study. This means that consumers always follow the latest technological developments. Greater enthusiasm for technology signals users' willingness to use emerging technologies, thereby increasing perceptions of usability and benefits. Innovativeness denotes the degree to which an individual assumes the lead in comprehending and actively pursuing novel technologies. A person with an innovative mindset tends to perceive that technology can facilitate the completion of certain tasks (Rahayu et al., 2022).

A different previous study (Pillai et al., 2020) which concluded that insecurity did not affect perceived usefulness but negative impact on perceived ease of use, the outcome of this study shows that insecurity does not affect perceived usefulness or perceived ease of use, meaning that e-commerce users, especially students, already feel safe shopping online on e-commerce supported by artificial intelligence. Users are more inclined to accept and incorporate technology into their everyday routines when it is perceived as safer (Jungst, 2022). Subsequently, empirical evidence suggests that the discomfort construct affects perceived usefulness and ease of use (Jeong & Kim, 2023). However, this is in contrast to the findings of a study (Mahmood et al., 2023) that claimed that discomfort does not affect perceived usefulness but does negatively affect perceived ease of use. The lower an individual’s discomfort, the more comfortable that person will feel and tend to be responsive and enthusiastic about the adoption of technology that can facilitate their affairs. If e-commerce users feel uncomfortable and anxious, they will tend not to adopt or use the novel technology.

CONCLUSION

This research intends to analyze the factors that influence the adoption of artificial intelligence in e-commerce. This study model employs the technology acceptance model and technology readiness as a framework. Through an online survey, data was gathered from 283 user e-commerce consumers in the provinces of Majalengka, Cirebon, Indramayu, and Kuningan. Nine of the eleven proposed hypotheses received acceptance, while two faced rejections. This research encourages the acceptance of AI in e-commerce based on consumer experience. The study found that the main factors influencing consumers' adoption and use of AI-based e-commerce are optimism, innovativeness, inconvenience, perceived usefulness, and perceived ease of use. The optimistic and innovative attitude of consumers, who see AI as a technology that can help them shop online, will increase their acceptance of AI in e-commerce. AI in e-commerce will continue to be used by consumers because it can provide them with convenience. AI can also provide quotes to give consumers the best price. This can reduce product research time, making their shopping more efficient.

This study makes a precious contribution to the fields of the technology acceptance model and the technology readiness model. The findings derived from this study also make a valuable contribution to the research field, as they have been measured and tested valid and reliably. The outcome of this study demonstrates the high reliability of the TAM theory model in assessing technology adoption, particularly in the matter of artificial intelligence technology in e-commerce. Hence, future research can incorporate the findings of this study and further review pertinent literature.

Web owners or e-commerce applications can use this study as input to determine whether consumers can adapt to artificial intelligence in e-commerce. This study can also help online businesses develop their business models by using artificial intelligence more efficiently and productively. The limitations in this study are limited to quantitative data obtained from respondents which can be biased because when filling out the questionnaire they are less serious in providing answers. So further researchers are advised to conduct direct interviews with e-commerce users.

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