

How AI Adoption Transforms Technology Acceptance into Online Purchase Behavior: An Integrated UTAUT–Technology Acceptance Model

Dewi Novianti^{1*}, Susanta², Didik Indarwanta³

¹ Communication, University of Pembangunan Nasional “Veteran” Yogyakarta, Indonesia

² Business Administration, University of Pembangunan Nasional “Veteran” Yogyakarta, Indonesia

³ Business Administration, University of Pembangunan Nasional “Veteran” Yogyakarta, Indonesia

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Abstract

Artificial intelligence (AI) is increasingly integrated into digital commerce through intelligent services that support consumer purchasing. However, limited empirical evidence explains how technology acceptance translates into AI adoption and subsequent online purchase behavior, particularly in digital MSMEs. This study examines the relationships among effort expectancy, performance expectancy, AI adoption, and online purchase behavior, positioning AI adoption as a behavioral link between technology acceptance and purchasing outcomes. A quantitative explanatory study was conducted using a cross-sectional survey of 126 consumers selected through purposive sampling. Respondents had used an AI-based service or feature, interacted with a digital MSME, and made an online purchase. Data were collected using a five-point Likert-scale questionnaire and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that performance expectancy significantly and positively affects AI adoption ($\beta = 0.657, p < 0.001$), whereas effort expectancy does not significantly affect AI adoption ($\beta = 0.101, p = 0.123$). Effort expectancy significantly and positively affects online purchase behavior ($\beta = 0.265, p < 0.001$), as does performance expectancy ($\beta = 0.168, p = 0.026$). AI adoption also significantly and positively affects online purchase behavior ($\beta = 0.317, p < 0.001$). These findings indicate that perceived performance benefits are more important for AI adoption, while both performance and ease of use contribute to online purchasing. The study contributes by positioning AI adoption as a behavioral mechanism connecting technology acceptance with online purchase behavior and offers practical implications for developing AI-enabled digital commerce services.

Keywords: *Artificial Intelligence Adoption, UTAUT, Technology Acceptance Model, Performance Expectancy, Online Purchase Behavior*

INTRODUCTION

Artificial Intelligence (AI) has become a transformative technology in digital commerce, enabling intelligent recommendation systems, chatbots, virtual assistants, and personalized shopping experiences that enhance customer engagement and purchasing decisions. Consequently, understanding the determinants of AI adoption has become an important research topic in information systems and e-commerce. Previous studies have extensively applied the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) to explain technology acceptance, showing that performance expectancy, effort expectancy, perceived usefulness, and perceived ease of use significantly influence consumers' behavioral intentions toward AI-enabled technologies (Shafi et al., 2025; Dixit et al., 2025; Hossain & Biswas, 2024).

Most prior studies treat AI adoption as the final outcome rather than as a strategic behavioral mechanism linking technology acceptance to online purchase behavior. The integration of UTAUT and TAM within a single sequential framework remains underexplored (Dixit et al., 2025;

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Corresponding author's email: dewi.novianti@upnyk.ac.id

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Chi, 2026; Hossain & Biswas, 2024; Hoa, 2025). To address this gap, the present study develops an integrated UTAUT–TAM model, positioning AI adoption as the central mechanism through which performance expectancy and effort expectancy influence online purchase behavior. This study aims to extend the explanatory power of technology acceptance theory and provide practical insights for designing AI-enabled e-commerce services that foster sustainable online purchasing behavior.

LITERATURE REVIEW

Relationship between Effort Expectancy and AI Adoption

Effort expectancy plays a crucial role in reducing perceived complexity and uncertainty, thereby increasing users' confidence in adopting AI technologies (D. Zhang et al., 2026; Tian et al., 2025; H. H. Nguyen & Nguyen, 2024; Qafas & El Moubarik, 2026). Recent empirical studies consistently show that effort expectancy positively influences AI adoption across contexts such as education, business, recruitment, AI chatbots, and construction. Users are more likely to adopt AI when they perceive it as easy to learn, understand, and integrate into daily activities (Zhuang et al., 2025; D. Zhang et al., 2026; Tian et al., 2025; Chen et al., 2025; X. Wu et al., 2025). Furthermore, integrating UTAUT and TAM confirms that effort expectancy and perceived ease of use jointly strengthen users' cognitive evaluations of AI technologies, leading to higher adoption intentions (D. Zhang et al., 2026; Khoa & Huynh, 2026; H. H. Nguyen & Nguyen, 2024; Papathomas et al., 2025; Qafas & El Moubarik, 2026).

Hypothesis (H1): Effort Expectancy has a positive and significant effect on AI Adoption.

Relationship between Performance Expectancy and AI Adoption

Performance expectancy is the extent to which individuals believe that using a technology will improve decision-making or overall effectiveness. Empirical evidence generally supports a positive relationship between performance expectancy and AI adoption across various organizational and professional contexts. Performance expectancy has been shown to predict AI adoption intention among professionals in Bangladesh (Emon et al., 2024) and to be an important antecedent of intention among healthcare workers and physicians adopting artificial-intelligence-assisted diagnosis and treatment (Cheng et al., 2022; Çiçin & Çetin-Gürkan, 2026). Consistent evidence also appears in human resource management, logistics, manufacturing, and service-related contexts, where users are more likely to adopt AI when they perceive that the technology can improve work processes, efficiency, and organizational outcomes (Xia, 2026; Sriwichien & Wisaeng, 2026; Yudhistyra & Srinuan, 2026). The relevance of performance expectancy is further supported by evidence that AI adoption can generate tangible outcomes, including improved employee performance (Mohaimen et al., 2026; Ghorbanzadeh et al., 2025), enhanced human resource management effectiveness (Xia, 2026; Chowdhury et al., 2026), and stronger perceived organizational performance in the manufacturing sector (Yudhistyra & Srinuan, 2026).

Hypothesis (H2): Performance Expectancy has a positive and significant effect on AI Adoption.

Relationship between Effort Expectancy and Online Purchase Behavior

Effort Expectancy reflects users' perceptions of how easy it is to learn, understand, and operate a technological system. It generally has a positive effect on online purchase behavior because ease of use reduces consumers' cognitive and operational burden when searching for information, evaluating products, and completing transactions. Empirical evidence supports this positive relationship across contexts such as cross-border e-commerce, tourism e-commerce, online shopping, social commerce, live-streaming commerce, and digital payments (Xu & Su, 2025; Hateftabar, 2023; Ying et al., 2021). Thus, effort expectancy is a context-dependent determinant:

the easier online shopping technologies are to use, the lower the barriers consumers face throughout the purchasing process, thereby increasing their likelihood of engaging in online purchasing.

Hypothesis H3: Effort Expectancy has a positive and significant effect on Online Purchase Behavior.

Relationship between AI Adoption and Online Purchase Behavior

AI adoption is generally associated with stronger online purchase intention and purchase-oriented behavior, particularly when consumers perceive AI-enabled technologies as useful, trustworthy, and capable of enhancing the shopping experience (Akram et al., 2021; Bunea et al., 2024; Fattouh et al., 2026). AI applications such as recommendation systems, chatbots, personalization, and AI-enabled services can facilitate purchasing by increasing perceived usefulness, trust, satisfaction, and customer engagement, although these factors may serve as mediators rather than AI adoption directly determining purchasing outcomes (Rana et al., 2024; Bhojwani et al., 2026; C. Zhang et al., 2026). Therefore, when AI adoption improves the efficiency and confidence of the online shopping process while reducing perceived effort and uncertainty, consumers are expected to exhibit stronger online purchase behavior.

Hypothesis H5: AI Adoption has a positive and significant effect on Online Purchase Behavior.

RESEARCH METHOD

This study employed an explanatory research design using a quantitative approach. The study used an infinite population. Purposive sampling was employed, with respondents required to (1) have used an AI-based service or feature, (2) have interacted with a digital MSME, (3) be at least 17 years old, and (4) have made an online purchase. According to Ainur et al. (2017) and Rosseel (2020), a sample of 100 to 200 is adequate for analysis using Partial Least Squares Structural Equation Modeling (PLS-SEM). A total of 126 respondents meeting the criteria participated in the study.

Data collection was conducted from June to July 2026. The questionnaire was distributed electronically via Google Forms and shared through WhatsApp, Instagram, and other digital communication channels. It consisted of 13 structured measurement items covering four constructs. The measurement items for Effort Expectancy and Performance Expectancy were adapted from Yu et al. (2021), AI Adoption from Yen et al. (2026), and Online Purchase Behavior from Indiani et al. (2024). All constructs were measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree.

PLS-SEM was used to assess measurement and structural models. Reliability and validity were evaluated using outer loadings, Cronbach's alpha, composite reliability, Average Variance Extracted, and the heterotrait-monotrait ratio. The structural model was examined for collinearity, R^2 , f^2 , Q^2 , and path coefficients. Hypotheses were tested via bootstrapping at the 5% significance level (Hadri & Abdem, 2025; Hair et al., 2021; Magno et al., 2024).

FINDINGS AND DISCUSSION

Instrument Test Results

Table 1 presents the validity and reliability results for the research instrument, based on a trial with 30 respondents. The findings indicate that all measurement items meet the validity criterion, with coefficients exceeding 0.3, and demonstrate adequate reliability, as evidenced by Cronbach's alpha values above 0.6.

Table 1. Research Instrument Test Results (N=30)

Variable and Indicator	Validity	Reliability
Effort Expectancy		
AI technology is easy to learn	0,403	0,950
Interacting with AI technology requires little effort	0,482	0,950
AI technology is easy to use in my activities	0,600	0,948
Performance expectancy		
AI technology improves my work effectiveness	0,726	0,947
AI technology helps complete tasks faster	0,717	0,947
AI technology increases my productivity	0,797	0,947
AI Adoption		
I have used AI technology in digital activities	0,755	0,946
I find AI technology beneficial in my life	0,739	0,946
I believe AI can assist with decision-making	0,849	0,945
Online Purchase Behavior		
I frequently purchase products online	0,456	0,950
I choose online platforms for shopping	0,426	0,950

Table 2 shows that male respondents outnumber female respondents. The majority of respondents were female undergraduate students between the ages of 20 and 29.

Table 2. Respondent Profile (n=126)

		%
Gender	Man	0.353
	Woman	0.647
Educational level	Senior High School	0.152
	Undergraduate Students	0.681
	Postgraduate Students	0.218
Age	Less than 20 years old	0.015
	20 – 29 years old	0.744
	30 – 39 years old	0.008
	40 – 49 years old	0.015
	More than 50 years old	0.218

Final Structural Model

The model fit and quality indices were evaluated using the WarpPLS analytical tool. The findings indicate that the proposed model is well supported by the empirical data, with all quality indicators meeting WarpPLS-established criteria.

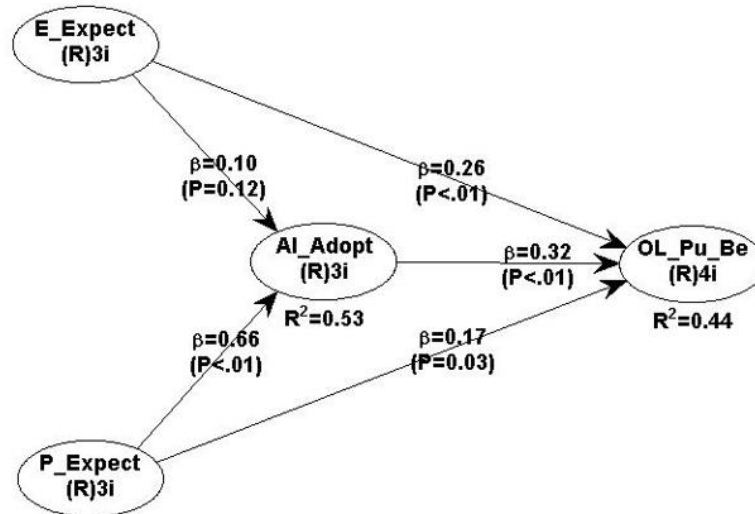


Figure 1. Final Structural Model

Hypothesis Testing

Hypothesis 1 proposes that Effort Expectancy has a positive and significant effect on AI Adoption. The results (Table 3) show that the p-value is greater than 0.005, indicating that Hypothesis 1 is rejected. Effort Expectancy affects AI Adoption, but the effect is not significant.

Hypothesis 2 proposes that Performance Expectancy has a positive and significant effect on AI Adoption. The results show that the p-value is less than 0.005, indicating that Hypothesis 2 is accepted. Positive coefficients suggest that higher Performance Expectancy is associated with higher AI Adoption.

Hypothesis 3 proposes that Effort Expectancy has a positive and significant effect on Online Purchase Behavior. The results show that the p-value is less than 0.005, indicating that Hypothesis 3 is accepted. Positive coefficients suggest that higher Effort Expectancy is associated with higher Online Purchase Behavior.

Hypothesis 4 proposes that Performance Expectancy has a positive and significant effect on Online Purchase Behavior. The results show that the p-value is less than 0.005, indicating that Hypothesis 4 is accepted. Positive coefficients suggest that higher Performance Expectancy is associated with higher Online Purchase Behavior.

Hypothesis 5 proposes that AI Adoption has a positive and significant effect on Online Purchase Behavior. The results (Table 3) show that the p-value is less than 0.005, indicating that Hypothesis 5 is accepted. Positive coefficients suggest that higher AI Adoption is associated with higher Online Purchase Behavior.

Table 3. Hypothesis Testing Results

Path	Coefficient	p-Value	Description
Effort Expectancy → AI Adoption	0,101	0.123	Rejected
Performance Expectancy → AI Adoption	0,657	<0.001	Accepted
Effort Expectancy → Online Purchase Behavior	0,265	<0.001	Accepted
Performance Expectancy → Online Purchase Behavior	0,168	0.026	Accepted
AI Adoption → Online Purchase Behavior	0,317	<0.001	Accepted

Discussion

Performance expectancy has a positive but insignificant effect on AI adoption

The finding that performance expectancy (PE) has a positive but statistically insignificant effect on AI adoption indicates that although users perceive AI as useful and capable of improving their performance, perceived usefulness alone is insufficient to significantly determine adoption. This result aligns with recent studies showing that PE can become a baseline expectation among users already familiar with AI, thereby reducing its ability to distinguish between adopters and non-adopters (BinJwair & Alamer, 2025; Ahmad et al., 2026; Gajić et al., 2024). In such circumstances, adoption decisions may be influenced more strongly by social influence, facilitating conditions, habit, trust, privacy concerns, and emotional factors than by perceived performance benefits (Li et al., 2026; Ahmad et al., 2026; Gajić et al., 2024). Moreover, PE may influence adoption indirectly through engagement, as recent evidence suggests that engagement can mediate the relationship between PE and behavioral intention to use ChatGPT (Alshammari et al., 2026). The coexistence of significant and insignificant PE effects across different AI contexts further suggests that its influence is context-dependent: PE can be a strong predictor when the benefits of AI are novel or highly salient (Cabero-Almenara et al., 2025; Weglarz et al., 2025; Demir & Findik Coşkunçay, 2026), but its direct effect may weaken when users already recognize AI's usefulness or when competing cognitive, social, contextual, and emotional factors become more influential. Thus, the positive but insignificant effect found in this study does not imply that PE is irrelevant; rather, it suggests that perceived usefulness of AI is not, by itself, sufficiently strong to drive adoption when other factors play a more decisive role in the adoption decision.

Performance Expectancy has a positive and significant effect on AI Adoption

The finding that Performance Expectancy has a positive and significant effect on AI Adoption indicates that the stronger users' belief that AI can improve their effectiveness, productivity, decision-making quality, and task performance, the greater their tendency to adopt AI. This finding is consistent with studies showing that performance expectancy is an important predictor of AI adoption intention across various contexts, including professional settings, healthcare, human resource management, logistics, manufacturing, and services, because users tend to adopt AI when they perceive that the technology can improve process efficiency and work outcomes (Emon et al., 2024; Cheng et al., 2022; Çiçin & Çetin-Gürkan, 2026). In the context of this study, the positive and significant effect indicates that when users perceive AI as genuinely helping them complete tasks more quickly, increase productivity, and improve the effectiveness of their activities, these perceived benefits can directly encourage their decision to adopt AI.

Effort Expectancy has a positive and significant effect on Online Purchase Behavior

The finding that Effort Expectancy has a positive and significant effect on Online Purchase Behavior indicates that consumers are more likely to engage in online purchasing when they perceive the digital shopping process as easy to learn, understand, and operate. Lower perceived effort reduces the cognitive and operational burden associated with searching for information, evaluating alternatives, and completing transactions. This positive relationship is supported by empirical evidence across various contexts, including cross-border e-commerce, tourism e-commerce, online shopping, social commerce, livestreaming commerce, digital payment, and online grocery applications, where greater ease of use is associated with stronger purchase intention or buying behavior (Cao & Putit, 2024; Xu & Su, 2025). The relationship can also be explained by the fact that reduced effort facilitates consumers' decision-making and transaction processes, making online purchasing more convenient and less demanding.

Performance Expectancy has a positive and significant effect on Online Purchase Behavior

The finding that Performance Expectancy has a positive and significant effect on Online Purchase Behavior suggests that consumers are more inclined to purchase products online when they believe digital platforms can make the shopping process more efficient, convenient, and effective. Previous empirical studies support this positive relationship across social commerce, online food delivery, tourism e-commerce, and fresh e-commerce, demonstrating that higher performance expectancy is associated with stronger purchase intentions or purchasing behavior (Akram et al., 2021; Xu & Su, 2025; L. Chen et al., 2021). This effect can be attributed to the tendency of consumers who perceive greater performance benefits to view online shopping as more useful and valuable, which subsequently encourages them to use digital platforms and engage in purchasing activities. The significant positive relationship identified in this study indicates that consumers' perceptions of the benefits provided by online shopping are sufficiently strong to influence their purchasing behavior.

AI Adoption has a positive and significant effect on Online Purchase Behavior

The finding that AI Adoption has a positive and significant effect on Online Purchase Behavior indicates that consumers who adopt and actively use AI-enabled technologies are more likely to engage in online purchasing because AI can facilitate the shopping process by providing personalized recommendations, intelligent assistance, relevant product information, and decision support. AI adoption can improve consumers' shopping efficiency and confidence by reducing information-processing effort and helping them navigate different stages of the online customer journey, thereby encouraging purchase-oriented behavior (Akram et al., 2021; Bunea et al., 2024; Fattouh et al., 2026). The positive and significant result in this study suggests that the benefits of AI adoption outweigh potential barriers in the observed context. Therefore, the findings reinforce the argument that greater adoption of AI-enabled technologies can enhance the effectiveness, convenience, personalization, and confidence of the online shopping process, ultimately increasing consumers' likelihood of engaging in online purchase behavior.

CONCLUSIONS

This study demonstrates that Performance Expectancy has a positive and significant effect on AI Adoption, while Effort Expectancy positively and significantly affects Online Purchase Behavior. Performance Expectancy and AI Adoption also have positive and significant effects on Online Purchase Behavior. These findings indicate that consumers are more likely to adopt AI when they perceive it improves effectiveness, productivity, and task performance, and that performance benefits and ease of use directly contribute to online purchasing.

Overall, the findings support the relevance of the integrated UTAUT-TAM perspective for explaining how consumers' evaluations of AI-enabled technologies relate to adoption and subsequent online purchasing behavior. The study contributes theoretically by positioning AI Adoption as a behavioral mechanism that links technology acceptance factors to online purchase behavior, extending UTAUT and TAM beyond technology adoption as an endpoint. Practically, digital platforms and MSMEs should emphasize AI features that deliver clear performance benefits, improve purchasing efficiency, and facilitate decision-making, while ensuring that AI-enabled services remain easy to use and relevant to consumers' needs.

LIMITATIONS & FURTHER RESEARCH

The study is limited by its cross-sectional survey and purposive sampling of 126 respondents. Future research should use larger, more diverse samples, probability-based sampling

where feasible, and longitudinal designs to examine changes in AI adoption and online purchase behavior over time. Future studies may also extend the model by incorporating trust, social influence, facilitating conditions, perceived risk, AI anxiety, satisfaction, and consumer engagement to provide a more comprehensive explanation of how AI adoption influences online purchase behavior.

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