**Asia Pacific Journal of Management and Education (APJME)**
**Vol. 8 No. 3, pp.446-462, November, 2025**
**E-ISSN: 2655-2035 P-ISSN: 2685-8835**
**https://www.ejournal.aibpm.org/index.php/APJME**

# The Role of Artificial Intelligence as a Mediator: Previous Psychological Factors and Purchase Intention

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**ARTICLE INFORMATION**

**Publication information**

**Research article**

**HOW TO CITE**
Faizah, N., Sunaryo, K., & Ghofar, A. (2025). The role of artificial intelligence as a mediator: Previous psychological factors and purchase intention. *Asia Pasific Journal of Management and Education*, *8*(3), 446-462.

**DOI:**
**https://doi.org/10.32535/apjme.v8i3.4204**

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Received: 17 September 2025
Accepted: 19 Oktober 2025
Published: 20 November 2025

**ABSTRACT**

Rapid developments in artificial intelligence (AI) have transformed e-commerce by enabling personalized recommendations and enhancing user engagement. However, consumer acceptance of AI-driven systems remains influenced by various psychological factors. This study aims to examine the effects of subjective norms, attitudes, and perceived behavioral control (PBC) on purchase intention through AI in e-commerce platforms. The research integrates the Theory of Planned Behavior (TPB) and the Technology Acceptance Model (TAM) to explain how these psychological variables shape users' acceptance of AI technology. Data were collected through an online survey of 250 respondents and analyzed using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach. The results reveal that subjective norms ($\beta = 0.274$, $p = 0.002$) and PBC ($\beta = 0.455$, $p = 0.000$) significantly and positively influence AI adoption, which in turn has a strong positive effect on purchase intention ($\beta = 0.664$, $p = 0.000$). Additionally, subjective norms ($\beta = 0.182$, $p = 0.008$) and PBC ($\beta = 0.302$, $p = 0.003$) indirectly affect purchase intention through AI. In contrast, attitude does not significantly affect AI adoption ($\beta = 0.095$, $p = 0.311$) or purchase intention ($\beta = 0.063$, $p = 0.310$). These findings extend TPB and TAM applications to AI-based contexts and provide practical insights for e-commerce firms to optimize AI-driven personalization and user experience.

**Keywords:** AI Adoption; E-commerce; Purchase Intention; Subjective Norms; Theory of Planned Behavior

## INTRODUCTION

The rapid advancement of digital technology has revolutionized how consumers engage with businesses, shifting traditional purchasing behavior toward data-driven and personalized online experiences. In the digital era, technology is used not only to improve operational efficiency but also to collect, process, and analyze consumer data in real time. These developments enable companies to deliver more personalized and relevant experiences to individual customers, thus increasing engagement and purchase conversion. According to McKinsey and Company (2024), approximately 61% of companies worldwide have implemented artificial intelligence (AI) in their marketing strategies, allowing them to gain deeper insight into consumer behaviour and provide increasingly accurate recommendations. This transformation demonstrates that AI has evolved from a back-end automation tool into a strategic instrument for creating value and building customer relationships.

In the global context, the integration of AI into e-commerce platforms has changed how businesses design, target, and deliver marketing content. Through recommendation engines, chatbots, and predictive analytics, AI helps firms identify consumer preferences, forecast demand, and optimize pricing strategies. Studies in developed economies show that AI-based personalization enhances user experience and strengthens brand loyalty (Lopes et al., 2024; Uzir et al., 2023). However, the adoption and acceptance of AI are not solely technological issues. They are strongly influenced by psychological and social factors that shape consumer decision-making.

In Indonesia, e-commerce has shown rapid and promising growth. According to the Indonesian E-Commerce Association (idEA), the value of e-commerce transactions reached around USD 35 billion in 2021 and is projected to double to USD 70 billion by 2025 (Suherly, 2023). The Institute for Development of Economics and Finance (INDEF) also highlights the significant multiplier effect of the digital economy on national growth, supported by increased internet penetration, affordable smartphones, and digital payment innovations (Rachbini, 2023). These factors accelerate online transactions and diversify product offerings, creating an increasingly interactive and satisfying shopping environment. Indonesian consumers now expect seamless digital experiences that are efficient, personalized, and trustworthy.

Nevertheless, the rapid expansion of e-commerce also brings new challenges related to user trust and psychological adaptation to digital technologies. User behavior in digital ecosystems is no longer determined solely by functional or technological aspects but is increasingly influenced by psychological and social dynamics. In this context, factors such as subjective norms, attitudes, and perceived behavioral control (PBC) become key predictors of how individuals perceive and adopt new technologies. These variables are central to Ajzen's (1991) theory of planned behavior (TPB), which posits that human behavior is guided by intentions formed through attitudes toward the behavior, perceived social pressure (subjective norms), and perceived control over performing the behavior.

Meanwhile, the technology acceptance model (TAM) provides another perspective on technology adoption, emphasizing the influence of perceived usefulness and perceived ease of use in shaping behavioral intentions. When integrated with TPB, TAM helps explain not only why individuals intend to use technology but also how external and psychological factors interact to shape acceptance and actual use. The integration of TPB and TAM thus provides a comprehensive framework for analyzing user acceptance of AI-driven systems, where decisions are shaped by both rational evaluations and social–psychological influences.

Despite AI's potential to personalize user experiences, enhance satisfaction, and improve engagement, several barriers remain that can weaken its impact on consumer purchase intention. One of the most critical issues is data privacy and security. Surveys indicate that around 76% of Indonesian consumers express concerns about the safety of their personal data when shopping online (Virdhani, 2024). Lee et al. (2022) argue that information overload and privacy violations can generate anxiety and reduce trust in e-commerce platforms. In Indonesia's context, these concerns are exacerbated by inconsistent data protection policies and limited consumer awareness of data rights, creating a perception of vulnerability. Such factors may prevent consumers from fully adopting AI-enabled shopping systems despite recognizing their potential benefits.

Existing studies have explored various dimensions of AI and consumer behavior, but remain fragmented. Lopes et al. (2024) demonstrated that AI positively affects purchase intention through enhanced personalization and trust. Zi et al. (2025) analyzed AI's role in customer retention across Asian markets, emphasizing the significance of personalized experiences and cultural adaptation. Sutiono et al. (2024) investigated the influence of social media influencers on purchase intentions in Indonesia, highlighting the mediating role of parasocial interaction. Similarly, Hakiki et al. (2024) examined product quality, promotion, and consumer trust as determinants of purchasing decisions on the Shopee platform. While these studies contribute valuable insights, they focus primarily on individual behavioral or marketing variables rather than integrated psychological frameworks explaining AI adoption. Bahri and Komaladewi (2023) examined the influence of Instagram social media, brand image, and price on online purchasing decisions among small and medium enterprises (SMEs) customers. The results showed that Instagram usage had no significant effect on online purchasing decisions, nor did brand image play a role in consumers' online purchasing decisions. Meanwhile, price was found to have a positive effect on online purchasing decisions. Therefore, researchers are interested in conducting further research to explore how perceived psychosocial factors can influence consumer purchase intentions mediated by AI in greater depth.

Moreover, few studies have attempted to bridge TPB and TAM in explaining consumer behavior in AI-mediated e-commerce. The majority of prior research either examines technology acceptance in isolation or applies psychological constructs without considering the mediating role of AI-based systems. Consequently, there is a theoretical gap in understanding how psychosocial factors jointly influence consumer behavior when mediated by AI. In emerging markets like Indonesia, where cultural collectivism and trust issues are dominant, this gap becomes even more relevant. Consumers may rely heavily on social validation (subjective norms) and perceived control over technology rather than personal attitudes alone. Therefore, combining TPB and TAM offers a more robust explanatory framework to understand these complex interactions.

From a practical standpoint, Indonesian e-commerce firms are facing increasing competition and must innovate to maintain consumer engagement. Many platforms, such as Tokopedia, Shopee, and Lazada, have begun adopting AI-driven features like personalized recommendations, virtual assistants, and predictive search. However, successful implementation requires not only technological advancement but also a deep understanding of consumer psychology. Firms that can align AI functions with users' social influence patterns, trust expectations, and perceived autonomy are more likely to succeed in fostering purchase intention and long-term loyalty.

Based on the discussion above, this research is motivated by the need to understand how psychological factors, subjective norms, attitudes, and PBC affect purchase intention through AI in the context of Indonesian e-commerce. The study integrates TPB and TAM to capture both the cognitive and behavioral dimensions of technology acceptance, providing a comprehensive theoretical perspective.

Theoretically, this study contributes to extending TPB and TAM applicability in AI-based digital environments, particularly within emerging markets characterized by strong social influence and evolving digital literacy. It offers empirical evidence on how psychosocial variables interact with AI as a mediating factor in shaping purchase intention. Practically, the research provides actionable insights for e-commerce companies to design AI-driven personalization strategies that build trust, simplify user interaction, and increase purchase conversion. By aligning AI systems with users' psychological and cultural contexts, firms can enhance consumer confidence, optimize user experience, and foster sustainable customer relationships in the digital marketplace.

## LITERATURE REVIEW

### Psychological Factor

Psychological factors encompass the individual-level processes and meanings that influence mental states. These factors are based on the TPB, which was developed by Ajzen (1991). It is an extension of the theory of reasoned action (TRA). The latter could not explain behaviors that were not entirely under an individual's control, hence the former's emergence. Ajzen then revised the theory in 2012 and 2020. In his 2012 research, Ajzen introduced new nuances to behavioral, normative, and control beliefs, highlighting that these three types of belief play different roles in influencing intentions and behavior depending on the social and cultural context. This update also delved deeper into aspects such as demographics, experience, and personality, which indirectly influence a person's beliefs and decisions. In his 2020 research, Ajzen further developed the theory by modifying it to incorporate technology, enabling it to address dynamic challenges and adapt to complex factors. According to the most recent research by Ajzen (2020), the TPB comprises three factors: subjective norm, attitude, and PBC.

### Purchase Intention

Purchase intention is the predicted or desired behavior of consumers and prospects, who can be influenced to react based on their ideas and behavior (McLean et al., 2020). It is a form of consumer behavior indicating a desire to purchase a product based on personal preference, experience of use, and passion for the product (Masuda et al., 2022). Purchase intention is a measure of the desire or likelihood of consumers to purchase a product (Kotler & Keller, 2012). It is also defined as a consumer's tendency or desire to purchase a product or service based on their evaluation of the available options (Solomon, 2017).

### Artificial Intelligence (AI)

In this era, digital marketing has emerged due to the advent of AI in marketing (Chen et al., 2012). Initially involving basic computational models to explore consumer behavior, the field has now evolved to the point where AI can be used to overcome traditional barriers to customer engagement (Russell et al., 1995). Furthermore, technology can personalize messages based on consumer demographics and behavioral characteristics (Kotler & Keller, 2012). The TAM framework can be used to analyze AI in marketing. This model consists of two main indicators: perceived ease of use and perceived usefulness.

According to Davis (1989), perceived ease of use is defined as the extent to which a person feels that using a particular system is effortless. Meanwhile, perceived usefulness is defined as the extent to which individuals believe that using a particular system can improve their performance at work. These two elements are interrelated and influence individuals' decisions to adopt new technologies, including AI in marketing.

## Hypotheses Development

### *Subjective Norm and AI*

According to Ajzen (2020), a subjective norm is an individual's perception of social pressure to perform, or not perform, a certain behavior. In other words, it reflects a person's belief about what important people in their life, such as family, friends, or colleagues, think about a certain behavior. It is an individual's perception of how important people view their specific behavior (Krueger Jr et al., 2000). Fishben and Ajzen (2010) categorize subjective norms into two types: injunctive and descriptive. An injunctive norm is an individual's perception of what should be done based on social approval or support. A descriptive norm, on the other hand, refers to an individual's perception of what others do in the same situation. Subjective norms relate to behaviors that are common or commonly performed by others. Including the influence of peers, colleagues, and social trends, subjective norm plays a crucial role in shaping individuals' attitudes towards AI-supported technology (Lopes et al., 2024). Their research suggests that subjective norms have a positive effect on AI. Based on this, the researchers formulated the following hypotheses:

H1: Subjective norms have a positive effect on AI.

### *Attitude and AI*

Tesser and Schwarz (2001) argue that attitudes towards behavior can be influenced by social, emotional, and personal experiences that shape a person's deeply held beliefs. (Fishben & Ajzen, 2010) suggest that attitudes encompass not only positive or negative evaluations of behavior, but also the intensity of beliefs regarding its consequences. For instance, if someone believes that an action will bring significant benefits, their attitude towards that behavior will be more positive. However, if they consider the outcome to be unimportant, their attitude will be more neutral. Ajzen (2020) defines attitude towards behavior as how someone views or evaluates a behavior based on their beliefs about its consequences. These beliefs are known as behavioral beliefs and are defined as a person's beliefs about the likelihood that performing a behavior will result in certain positive or negative outcomes or experiences.

A person's attitude reflects their preference for certain ideas, objects, or actions. In consumer behavior studies, attitude plays a central role because it influences consumers' thoughts, feelings, and, most importantly, decision-making processes. Attitude is considered an overall evaluation or assessment involving psychological attachment to an object and an assessment of whether or not the object is liked. Research by McLean et al. (2020) indicates that attitudes positively impact e-commerce applications, though the effect varies between the early adoption and sustained use phases. Research by Pathak et al. (2025) indicates that attitudes positively influence chatbot usage. Based on these findings, the researchers formulated the following hypotheses:

H2: Attitude has a positive effect on AI.

### *PBC and AI*

Bandura (1997) links PBC with self-efficacy, defined as a person's belief in their ability to achieve certain results. He emphasizes that it is not just a perception of external barriers, but also an individual's belief in their internal abilities, such as their skills and knowledge, that can support the achievement of desired results. In this context, both self-efficacy and PBC function as self-control mechanisms that influence an individual's intentions and decisions to act. Ajzen (2020) defines PBC as a person's perception of the ease or difficulty of performing a particular behavior. This concept is determined by the availability of resources and opportunities, as well as factors that can facilitate or hinder the behavior. It encompasses an individual's belief in their ability to perform a behavior while taking into account both external factors, such as time, money, or help from others, and internal factors, such as skills or self-confidence.

Users who feel they have a higher level of control over an AI system are more likely to explore its full potential and integrate it into their daily tasks. This increased interaction is often driven by a reduced perception of risk and greater trust in the technology. It also encourages users to experiment and learn, ultimately providing a deeper understanding of the capabilities and limitations of AI systems. When users feel they have control over AI, they tend to perceive the system as user-friendly, which encourages further use and acceptance of the technology. Lopes et al. (2024) argue that PBC positively affects AI. Based on this, the researchers formulated the following hypotheses:

H3: PBC has a positive effect on AI.

***AI and Purchase Intention***

In 1989, Davis raised concerns about users' reluctance to accept and use technology, such as devices or tools. This resistance decreased when users found certain devices easy to use. Therefore, ease of use refers to the degree to which individuals believe that a particular technology is easy to use. Meanwhile, perceived usefulness is a cognitive factor that determines acceptance of, or intention to use, an innovation or device. Perceived usefulness is defined as a person's belief that using new technology will improve their performance and productivity. Davis (1989) suggested that people would be interested in adopting new technology or devices if they believed these would be useful. Purchase intention refers to a person's or organization's desire to buy or use new technology, innovations, or products (Uzir et al., 2023). Many researchers argue that this intention greatly influences whether someone will actually make a purchase. Therefore, if someone intends to buy a certain product, they are more likely to do so than someone with no such intention.

AI-supported features such as chatbots for instant customer service, recommendation engines for personalized product suggestions, and voice search for hands-free navigation play a significant role in enhancing the online shopping experience. They influence user satisfaction by meeting individual needs and preferences. This makes the online shopping experience more engaging and less burdensome for consumers. Research by Uzir et al. (2023) shows that AI positively affects purchase intention. Similarly, Lopes et al. (2024) argue that AI has a positive effect on purchase intention. Based on this, the researchers formulate the following hypotheses:

H4: AI has a positive effect on purchase intention.

***The Mediating Effect of AI***

Subjectively, when technology is involved, norms encompass the influence of friends, colleagues, and social trends, all of which play a role in shaping attitudes towards AI-supported technology. These attitudes influence perceptions of ease of use, which ultimately impact satisfaction and acceptance levels (Lopes et al., 2024). AI acts as an intermediary that connects subjective norms with purchase intentions for products. This makes consumers more likely to proceed with a purchase. The combination of subjective norms, the ease with which AI can be used, and purchase intentions shows that consumer choices are greatly influenced by their social environment and by technology that facilitates the shopping experience. Research by Lopes et al. (2024) shows that subjective norms positively impact purchase intention when mediated by the ease of use of AI-supported technology. Based on this, the researchers formulated the following hypotheses:

H5: Subjective norms have a positive effect on purchase intention through AI.

Attitude reflects the positive or negative evaluation held by individuals (Adawiyah et al., 2024). Consumer attitude greatly influences the perceived usefulness and ease of use of AI technology, which directly impacts purchase intention. Previous research by Adawiyah et al. (2024) indicates that attitude influences intention via AI. Based on this, the researchers formulated the following hypotheses:

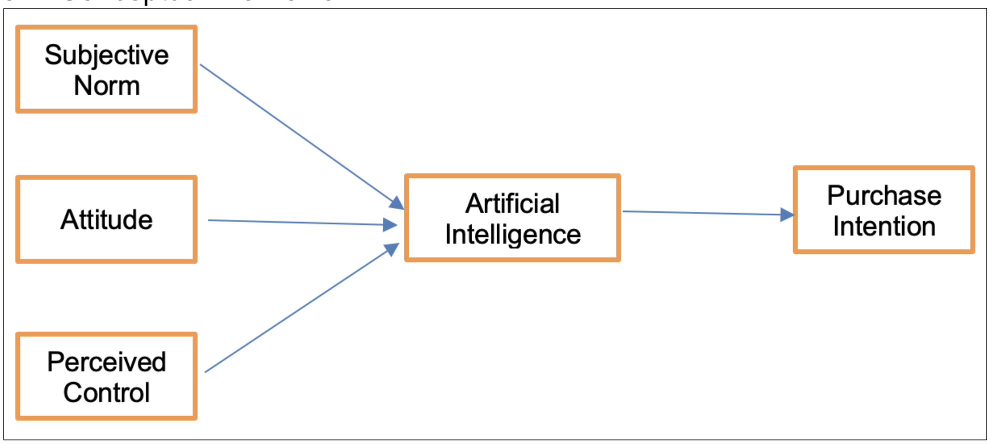
H6: Attitude has a positive effect on purchase intention via AI.

According to Lopes et al. (2024), the integration of AI into online shopping platforms has introduced a new dimension to the way in which perceived control influences consumer purchase intentions. The ease of use provided by AI is an important mediator in this relationship, enhancing the shopping experience by making navigation, information retrieval, and decision-making more intuitive and less effortful. This mediation occurs because AI technology personalizes the shopping experience by providing recommendations and assistance that are tailored to consumers' past preferences and behavior. This personalization increases users' perceived control over the shopping process by making it seem more manageable and tailored to their needs and desires. Research by Lopes et al. (2024) found that perceived control positively influences purchase intention when mediated by AI-supported ease of use. Based on this finding, the researchers formulated the following hypotheses:

H7: PBC positively influences purchase intention through AI.

**Conceptual Framework**
Figure 1 illustrates the conceptual framework of this study.

**Figure 1.** Conceptual Framework




## RESEARCH METHOD

This study involved students from the Faculty of Economics and Business, Universitas Pembangunan Nasional (UPN) “Veteran” Yogyakarta, as the research population. Students were selected because they represent an appropriate and accessible group for examining technology-related behavioral intentions. They are considered digital natives who actively engage in online transactions and frequently interact with e-commerce platforms, making them relevant respondents for investigating psychological factors influencing purchase intentions mediated by AI. Moreover, students enrolled in digital business courses are familiar with AI-based applications and online marketing concepts, allowing them to provide informed and reliable responses to the study variables. The researcher's affiliation with the same institution also facilitated efficient data collection while ensuring respondent accessibility and comprehension of the research context. Sampling was conducted using a purposive sampling technique based on specific criteria: (1) students enrolled in digital business courses and (2) active users of e-commerce platforms.

Data were collected using a questionnaire with statements measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Following Hair et al. (2021), the minimum sample size was determined as 5–10 times the number of indicators. With 15 indicators, the minimum required sample size was 75 respondents; therefore, 95 questionnaires were distributed to anticipate non-responses. All participants were informed of the study's purpose, and participation was entirely voluntary. Respondents were assured of confidentiality and anonymity, and their responses were used solely for academic purposes.

The subjective norm variable consists of three indicators (motivation to comply, descriptive norm, and injunctive norm), which refer to Bhattacharya's (2022) study. The attitude variable consists of four indicators (behavioral belief, outcome evaluation, affective, and instrumental), which refer to Ajzen's (2020) research. The PBC variable consists of three indicators (control belief, perceived power, and self-efficacy), which refer to Ajzen's (2020) research. The AI variable consists of two indicators (perceived usefulness and perceived ease of use), which refer to Davis' (1989) research. The purchase intention variable consists of four indicators (intention, consideration, probability), which refer to Senali et al.'s (2024) research.

Data analysis was performed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The analysis consisted of two stages: (1) the outer model to test indicator validity and reliability, and (2) the inner model to evaluate the structural relationships among latent variables and test the research hypotheses.

## RESULTS

**Table 1.** Descriptive Statistics (N =87)

| Variable | Code | Indicator | Mean | Std. Deviation | Category |
|---|---|---|---|---|---|
| Subjective Norm | SN1 | Motivation to Comply | 4.0460 | 1.05553 | Strong |
| | SN2 | Descriptive Norms | 4.0230 | 0.92732 | Strong |
| | SN3 | Injunctive Norms | 3.9655 | 1.02807 | Strong |
| Attitude | A1 | Behavioral Beliefs | 4.0345 | 1.03932 | High |
| | A2 | Outcome Evaluation | 3.8966 | 1.03468 | High |
| | A3 | Affective | 3.9080 | 0.94785 | High |
| | A4 | Instrumental | 4.0115 | 0.93379 | High |
| Perceived Control | PC1 | Control Believe | 4.1149 | 0.90766 | Strong |
| | PC2 | Perceived Power | 4.0575 | 0.90677 | Strong |
| | PC3 | Self-Efficacy | 4.1494 | 0.93422 | Strong |
| AI | AI1 | Perceived Usefulness | 4.1149 | 0.98152 | Strong |
| | AI2 | Perceived Ease of Use | 4.0575 | 1.00413 | Strong |
| Purchase Intention | PI1 | Intention | 4.0460 | 1.02195 | High |
| | PI2 | Consideration | 4.1034 | 0.94049 | High |
| | PI3 | Likelihood | 4.0575 | 0.96877 | High |

The results of the descriptive analysis in Table 1 indicate a high average subjective norm value of 4.0115. This suggests that respondents feel under significant social pressure to

**Asia Pacific Journal of Management and Education (APJME)**
**Vol. 8 No. 3, pp.446-462, November, 2025**
**E-ISSN: 2655-2035 P-ISSN: 2685-8835**
**https://www.ejournal.aibpm.org/index.php/APJME**

use AI. With an average value of 3.9627, respondents' confidence in using AI is very high. With an average perceived control score of 4.1072, it is clear that respondents had a very strong perception of their ability to use AI. With an average score of 4.0885, respondents' perception of the benefits of AI was found to be very strong. With an average purchase intention score of 4.0689, it is clear that respondents were highly motivated to make a purchase.

**Outer Model Testing**

Outer model testing consists of discriminant validity testing, convergent validity testing, and reliability testing. The results of the outer model testing are presented in Tables 2 and 3 below.

**Table 2.** Discriminant Validity Results

| | Attitude | AI | Perceived Control | Purchase Intention | Subjective Norm |
|---|---|---|---|---|---|
| A1 | 0.849 | 0.483 | 0.578 | 0.52 | 0.563 |
| A2 | 0.855 | 0.459 | 0.528 | 0.444 | 0.48 |
| A3 | 0.904 | 0.505 | 0.538 | 0.51 | 0.521 |
| A4 | 0.822 | 0.383 | 0.481 | 0.447 | 0.417 |
| AI1 | 0.453 | 0.921 | 0.63 | 0.657 | 0.568 |
| AI2 | 0.533 | 0.908 | 0.626 | 0.554 | 0.558 |
| PC1 | 0.51 | 0.568 | 0.818 | 0.571 | 0.468 |
| PC2 | 0.549 | 0.579 | 0.855 | 0.634 | 0.551 |
| PC3 | 0.53 | 0.609 | 0.885 | 0.561 | 0.585 |
| PI1 | 0.482 | 0.613 | 0.607 | 0.888 | 0.519 |
| PI2 | 0.561 | 0.609 | 0.62 | 0.886 | 0.603 |
| PI3 | 0.428 | 0.52 | 0.587 | 0.862 | 0.491 |
| SN1 | 0.477 | 0.519 | 0.558 | 0.497 | 0.843 |
| SN2 | 0.473 | 0.463 | 0.508 | 0.521 | 0.869 |
| SN3 | 0.522 | 0.571 | 0.527 | 0.541 | 0.834 |

As shown in Table 2, the cross-loading of each variable is greater than 0.70, meaning that it correlates more strongly with the main variable it measures than with other variables. This indicates that the variable has good discriminant validity. These results align with Ghozali’s (2014) findings that cross-loading for each variable must be greater than 0.70, as determined by a table with rows for indicators and columns for constructs/latent variables.

**Table 3.** Convergent Validity and Reliability Results

| Variable | Indicator | Outer Loading | Cronbach's Alpha | Composite Reliability | AVE |
|---|---|---|---|---|---|
| Subjective Norm | SN1 | 0.843 | 0.807 | 0.885 | 0.72 |
| | SN2 | 0.869 | | | |
| | SN3 | 0.834 | | | |
| Attitude | A1 | 0.849 | 0.881 | 0.918 | 0.736 |
| | A2 | 0.855 | | | |
| | A3 | 0.904 | | | |
| | A4 | 0.822 | | | |
| Perceived Control | PC1 | 0.818 | 0.813 | 0.889 | 0.728 |
| | PC2 | 0.855 | | | |
| | PC3 | 0.885 | | | |
| AI | AI1 | 0.921 | 0.805 | 0.911 | 0.837 |
| | AI2 | 0.908 | | | |

| | | | | | |
|---|---|---|---|---|---|
| Purchase Intention | PI1 | 0.888 | 0.853 | 0.91 | 0.772 |
| | PI2 | 0.886 | | | |
| | PI3 | 0.862 | | | |

The results in Table 3 provide strong evidence of the validity and reliability of the indicators employed in this study. The outer loading values range from 0.818 to 0.921, all of which exceed the minimum limit of 0.7 suggested by Hair et al. (2021). This indicates that each indicator is sufficiently correlated with the related latent construct, thus meeting the criteria for convergent validity. The average variance extracted (AVE) values range from 0.72 to 0.837, which is also above the minimum threshold of 0.50. This further supports the idea that the indicators adequately capture the variance in their respective constructs. In terms of reliability, the Cronbach's alpha values ranged from 0.805 to 0.881, which meets the minimum threshold of 0.70 recommended by Ghozali (2014) and indicates internal consistency among the indicators. Meanwhile, the composite reliability values ranged from 0.885 to 0.918, exceeding the minimum threshold of 0.70 and indicating the construct's overall reliability. Thus, these results confirm that the indicators used in this study meet the validity and reliability criteria, making them suitable for further analysis.

### Inner Model Testing

**Table 4.** Inner Model Results

| | R Square | R Square Adjusted | $Q^2$ |
|---|---|---|---|
| AI | 0.532 | 0.519 | 0.435 |
| Purchase Intention | 0.441 | 0.436 | 0.324 |

As shown in Table 4, the AI and purchase intention have R-squared values greater than 0.40, meaning that the model is of medium strength. $Q^2$ is considered good because it has a value greater than 0. The model shows strong predictive relevance for AI and purchase intention ($Q^2 > 0.3$).

### Hypothesis Testing

The results of the research model using SEM-PLS are illustrated in Figure 2 below.

**Figure 2.** Research Model

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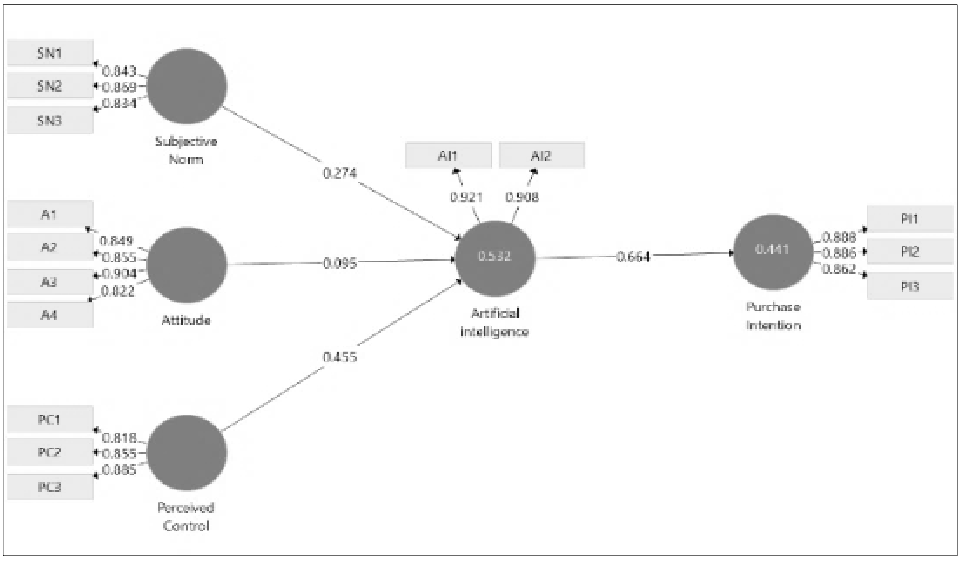


**Table 5.** Hypothesis Testing Results

| Hypothesis | Original Sample (O) | t Statistics | P-Val | Result |
|---|---|---|---|---|
| H1 | 0.274 | 3.150 | 0.002 | Accepted |
| H2 | 0.095 | 1.015 | 0.311 | Rejected |
| H3 | 0.455 | 3.745 | 0 | Accepted |
| H4 | 0.664 | 7.859 | 0 | Accepted |
| H5 | 0.182 | 2.673 | 0.008 | Accepted |
| H6 | 0.063 | 1.017 | 0.31 | Rejected |
| H7 | 0.302 | 3.017 | 0.003 | Accepted |

Hypothesis testing results presented in Table 5 indicate that five of the seven proposed hypotheses (H1, H3, H4, H5, and H7) are accepted, while the remaining two (H2 and H6) are rejected. H1 has an original sample value of 0.274, a t-statistic of 3.150, and a p-value of 0.002, all of which meet the significance criteria (t-statistic ≥ 1.96 and p-value ≤ 0.05). Therefore, H1 is accepted, indicating a positive and significant relationship. H3 also shows a positive and significant effect, with an original sample value of 0.455, a t-statistic of 3.745, and a p-value of 0.000. Similarly, H4 demonstrates a very strong and significant relationship, with an original sample value of 0.664, a t-statistic of 7.859, and a p-value of 0.000. Furthermore, H5 is accepted with an original sample value of 0.182, a t-statistic of 2.673, and a p-value of 0.008, confirming a positive and significant relationship. H7 is also accepted, showing an original sample value of 0.302, a t-statistic of 3.017, and a p-value of 0.003, which satisfies the minimum criteria for significance (t-statistic ≥ 1.96 and p-value ≤ 0.05).

Conversely, H2 and H6 are rejected as their statistical values do not meet the significance thresholds. H2 has an original sample value of 0.095, a t-statistic of 1.015, and a p-value of 0.311, suggesting that the relationship between the variables is not statistically significant. Likewise, H6 has an original sample value of 0.063, a t-statistic of 1.017, and a p-value of 0.310, indicating a non-significant relationship between the tested variables.

Overall, these findings reveal that most of the hypothesized relationships in the research model are significant, thereby supporting the majority of the proposed hypotheses. The established decision criteria for hypothesis acceptance are a t-statistic value of at least 1.96 and a p-value of 0.05 or lower.

## DISCUSSION

### H1: The Positive Influence of Subjective Norms on AI Adoption

The findings of this study reveal that subjective norms exert a significant and positive influence on both AI acceptance and purchase intention, directly and indirectly through AI mediation. This underscores the powerful role of social influence originating from peers, classmates, family members, or social networks in shaping consumers' willingness to engage with AI-based features within e-commerce platforms. In Indonesia's collectivist cultural context, where interpersonal harmony and conformity to group expectations are valued, individuals often make purchasing or adoption decisions that align with social validation rather than personal attitudes alone. Thus, when AI technologies are perceived as socially endorsed, beneficial, or fashionable within one's social environment, consumers are more inclined to adopt and use them.

This outcome reinforces the TPB, which posits that subjective norms are a central determinant of behavioral intentions, and extends its application to the domain of AI-based e-commerce. The findings are consistent with Lopes et al. (2024), who emphasized the importance of social influence in AI adoption, particularly in emerging markets. Moreover, they highlight that AI adoption is not merely a technological decision but also a social behavior, embedded in networks of peer influence, cultural norms, and digital community perceptions. For practitioners, this implies that e-commerce platforms should leverage social proof strategies, such as testimonials, user-generated reviews, influencer collaborations, or AI-assisted "friends also bought" features. By displaying peer usage data or social endorsement cues, companies can amplify trust and strengthen consumer engagement in AI-mediated shopping environments.

### H2: The Insignificant Role of Attitude Toward AI Adoption

Conversely, the study finds that attitude toward AI does not significantly influence AI adoption or purchase intention either directly or indirectly. This phenomenon indicates a potential attitude-behavior gap, where favorable perceptions of AI do not necessarily translate into behavioral engagement. Several contextual factors may explain this discrepancy. First, many Indonesian consumers remain at the early adoption stage of AI utilization, possessing a limited understanding of its full capabilities or benefits. Consequently, even positive attitudes may be accompanied by cognitive uncertainty or hesitation. Second, privacy and data security concerns are prevalent in Indonesia's digital ecosystem. According to Lee et al. (2022), high anxiety about personal data misuse can diminish behavioral intentions, even when attitudes are positive. Third, Indonesia's cultural inclination toward trust-based and interpersonal interactions may contribute to the preference for human-mediated online shopping experiences rather than algorithm-driven personalization.

These findings challenge the conventional assumptions of the TAM framework, which often identifies attitude as a dominant predictor of behavioral intention in Western or digitally advanced markets (McLean et al., 2020; Pathak et al., 2025). The inconsistency underscores that technology acceptance is culturally and contextually contingent. In markets characterized by collectivism and moderate digital maturity, social validation and perceived control may outweigh individual attitudes in predicting technology adoption. Hence, future theoretical models integrating TPB and TAM should explicitly account for cultural moderators and trust-related factors when analyzing AI adoption behavior across diverse regions.

### H3: The Significant Impact of PBC on AI Adoption

Meanwhile, PBC also demonstrates a significant and positive impact on AI adoption and purchase intention, both directly and through mediation. This indicates that consumers who perceive themselves as capable of operating AI-based systems and who possess the necessary digital resources, such as internet access, device proficiency, and digital literacy, are more likely to utilize AI in their purchasing process. This finding aligns with Ajzen's (1991) TPB and resonates with Lopes et al. (2024), emphasizing that perceived competence and self-efficacy are critical antecedents of technology acceptance. From a TAM perspective, perceived control can be linked to perceived ease of use, which facilitates user interaction with technology.

In this context, AI-mediated personalization plays a dual role: it simplifies decision-making while simultaneously enhancing perceived efficiency and autonomy in online shopping. When users feel empowered and confident navigating AI recommendations, their purchase intention tends to increase. Therefore, e-commerce firms should focus on user empowerment strategies, such as developing intuitive, transparent, and user-friendly AI interfaces. Providing step-by-step guides, chatbots that offer real-time assistance, and culturally localized design (e.g., multilingual interfaces or culturally familiar visuals) can significantly enhance users' perceived control. Such efforts not only improve technology acceptance but also foster long-term trust and engagement with AI systems.

**H4: The Effect of AI Adoption on Purchase Intention**

AI adoption demonstrates a significant and positive effect on purchase intention, indicating that the integration of AI in e-commerce enhances consumer engagement and decision-making. This relationship suggests that when users perceive AI as reliable, helpful, and efficient, they are more inclined to make purchasing decisions guided by its recommendations. The interaction with AI systems, such as chatbots, recommendation algorithms, and virtual assistants, can increase perceived convenience and personalization, which in turn strengthens purchase intention. These results are consistent with the theoretical foundations of both TPB and TAM, emphasizing the role of perceived usefulness and behavioral control in translating technology interaction into purchasing behavior.

**H5: The Mediating Role of AI Adoption Between Subjective Norms and Purchase Intention**

The results further confirm that AI adoption mediates the relationship between subjective norms and purchase intention. This implies that social influence not only shapes the perception of AI but also encourages its use as a means to align with group expectations. When individuals perceive that AI-based technologies are socially valued or widely accepted, they are more likely to adopt them, which then drives higher purchase intention. This finding highlights the role of AI as a mediating tool in transforming social pressure into actual behavioral outcomes. It also suggests that e-commerce firms can optimize AI-mediated shopping experiences by embedding socially driven features, such as "most popular" or "trending among friends", to stimulate conformity-based purchasing motivation.

**H6: The Non-Significant Mediation of AI Between Attitude and Purchase Intention**

Although attitudes toward AI appear positive, their indirect influence on purchase intention through AI adoption is not significant. This suggests that favorable perceptions alone are insufficient to drive behavioral change without adequate trust, familiarity, or technological readiness. This aligns with the previously mentioned attitude-behavior gap, where consumers may appreciate the AI conceptually but refrain from full adoption due to limited experience, perceived risks, or data privacy concerns. In Indonesia's context, consumers still place higher value on interpersonal trust than on technological convenience, making it necessary for companies to design interventions that build both affective trust and perceived control simultaneously.

**H7: The Mediating Role of AI Adoption Between PBC and Purchase Intention**
The mediation analysis also confirms that AI adoption significantly mediates the relationship between PBC and purchase intention. Consumers who feel capable and confident in using AI-based systems are more likely to adopt the technology, which in turn enhances their likelihood of purchasing through e-commerce platforms. This finding reinforces the importance of user empowerment and the perception of control in driving engagement. From a managerial perspective, improving accessibility, interface simplicity, and digital literacy can enhance both direct and indirect effects of perceived control on purchase behavior.

**Managerial and Cross-Cultural Implications**
From a managerial perspective, these insights provide actionable implications for practitioners in Indonesia's e-commerce industry. Firms should prioritize strengthening subjective norms through community engagement features, such as digital forums, peer-to-peer sharing, or AI-driven social recommendation systems. Social endorsement campaigns that highlight how users' friends or communities interact with AI features can boost collective trust. Moreover, improving PBC through accessible design and continuous user education via in-app tutorials, gamified learning, or customer support chatbots can further enhance user confidence.

Addressing privacy concerns remains critical for sustaining trust. Companies should ensure transparent communication regarding data usage, provide users with granular control over personalization settings, and visibly display security assurances to mitigate anxiety. By integrating ethical AI design principles, firms can balance personalization and privacy, ultimately transforming AI from a transactional tool into a trustworthy digital companion that aligns with users' social and psychological expectations.

Finally, when compared to findings from global contexts, this study highlights regional nuances in AI acceptance dynamics. In developed economies such as the United States, Japan, and South Korea, studies by Pathak et al. (2025) and Uzir et al. (2023) demonstrate that attitude and perceived usefulness are dominant predictors of AI adoption. In contrast, in emerging economies like Indonesia, where collectivism and digital inequality persist, subjective norms and perceived control appear to play more substantial roles. This divergence suggests that AI adoption strategies cannot be universalized; rather, they must be localized to reflect socio-cultural realities.

Therefore, global e-commerce firms aiming to expand in Southeast Asia must embrace context-sensitive AI strategies, emphasizing social engagement, cultural adaptation, and user empowerment. Incorporating culturally relevant personalization, community-based marketing, and transparent data governance will not only enhance AI adoption but also foster sustainable consumer trust and long-term loyalty. These findings affirm that effective AI deployment depends not merely on technological sophistication but on its alignment with human psychology, culture, and values, marking a pivotal direction for future AI and consumer behavior research.

## CONCLUSION

This study aimed to examine the influence of subjective norms, attitude, and PBC on the acceptance of AI-based technology and its impact on purchase intention within the e-commerce context. The results reveal that subjective norms and PBC significantly influence AI acceptance and purchase intention, both directly and indirectly. However, attitude does not show a significant effect on AI acceptance, indicating that social influence and perceived control play a more dominant role than individual attitude in shaping consumers' behavioral intentions toward AI technology.

In theoretical terms, this research extends the application of the TPB and the TAM to the field of AI-based technology adoption. It provides empirical validation that subjective norms and PBC are critical determinants of consumer behavior in digital marketing contexts. Furthermore, by demonstrating that attitude does not significantly affect AI acceptance, this study challenges conventional assumptions in prior technology adoption literature and offers new insights into the psychological dynamics underlying AI usage in e-commerce.

Practically, the findings provide e-commerce companies with valuable guidance on how to enhance consumer engagement with AI-based technologies. Strengthening subjective norms through social validation strategies, such as customer testimonials, influencer collaborations, or peer recommendations, can effectively increase users' trust and willingness to adopt AI features. Meanwhile, improving consumers' perceived behavioral control by offering intuitive user interfaces, comprehensive tutorials, and responsive customer service can boost confidence and facilitate smoother adoption. By integrating user-friendly AI designs and culturally relevant personalization, companies can enhance customer experience and encourage higher purchase intentions.

For future research, it is suggested to explore additional variables such as trust, perceived risk, and cultural values that may further explain the adoption of AI technology in e-commerce. Comparative studies across different countries or digital maturity levels could also provide a broader understanding of how cultural and contextual factors influence the acceptance of AI-based systems.

## LIMITATION

This study is not without limitations; the sample was limited to students from UPN Veteran Yogyakarta, which may restrict the generalizability of the findings. Therefore, future studies are encouraged to involve more diverse respondent groups and consider extending the research model by replacing the dependent variable with repurchase intention or customer loyalty to capture longer-term behavioral outcomes.

## ACKNOWLEDGMENT

The Authors would like to thank the Faculty of Economics and Business, Gadjah Mada University, and UPN "Veteran" Yogyakarta.

## DECLARATION OF CONFLICTING INTERESTS

The authors have no problem with any party in completing this research. The data used in this research have no conflict of interest with any party.

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