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# Factors influencing Gen Z's adoption of AI - Behavioral insights from Indonesia's digital banking sector

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## Abstract

Despite the recognition of artificial intelligence (AI) as an innovative banking frontier, its full-scale activation is limited by an insufficient understanding of user adoption behaviors, particularly among specific demographics in emerging markets. This study explores the behavioral indicators affecting the adoption of AI among potential digital banking adopters in Indonesia classified as Gen Z. The theoretical underpinnings of the unified theory of acceptance of technology (UTAUT2) and technology acceptance model (TAM), data from 414 respondents, and the structural equation modeling (SEM) technique were used to identify the behavioral indicators of AI adoption. The empirical findings reveal that intrinsic motivations (perceived ease of use, usefulness, performance expectancy, effort expectancy, and hedonic motivation) significantly drive AI adoption among Gen Z in Indonesian digital banking. Notably, external factors such as social influence and facilitating conditions, along with demographic variables such as gender and age, were found to be insignificant, challenging the established models in this context. Conversely, the level of education and job role emerged as significant drivers. This study refines the integrated UTAUT2 and TAM framework by demonstrating how the unique characteristics of Gen Z in an emerging digital economy reshape the influence of external factors, thereby establishing crucial boundary conditions for these models. These findings offer actionable insights for banking professionals to design targeted digital marketing strategies and policies that resonate with this crucial demographic, especially in contexts similar to Indonesia's digital development stage.

**Keywords**: AI adoption; Digital banking; Digital marketing; Gen Z; Technology acceptance

**JEL Classification: G91, D21, M31**

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## INTRODUCTION

The financial industry is undergoing a profound digital transformation, with artificial intelligence (AI) fundamentally reshaping the operational and business landscapes of banking institutions (Zhou & Liao, 2024; Shi & Wang, 2025). AI is widely recognized for its potential to enhance efficiency, manage risk, and foster customer loyalty (Batra & Goel, 2023; J.P. Morgan, 2023), driving substantial global investment in AI-enabled financial services (IDC, 2023). Under the umbrella of the digital economy, banks are increasingly deploying AI to improve service delivery and operational effectiveness. Existing research and policy discussions predominantly focus on technological capabilities and economic benefits, offering limited insights into how end users perceive and interact with AI-based banking services.

The existing body of research and policy discussions regarding AI in banking exhibits several critical gaps, primarily concerning the understanding of actual user adoption behavior. Prior studies have predominantly focused on macro-level aspects, such as financial performance, institutional strategies, and regulatory impacts, consequently overlooking the intricate behavioral indicators that truly shape user engagement with AI-powered services (Fares et al., 2023). Additionally, policy documents from prominent financial consulting groups and regulatory bodies emphasize institutional adoption, financial outcomes, and governance requirements (FSB, 2025; Kanellopoulou et al., 2025), rather than addressing the integration of AI among social stakeholders or understanding user-centric perspectives. A significant theoretical limitation is also evident (Byambaa et al., 2025; Lee & Chen, 2022), as much of the current AI adoption research originates from developed economies or examines broader, undifferentiated populations. This leads to a lack of theoretical insight into the specific mechanisms and motivations underlying adoption intentions among distinct demographics, particularly Generation Z users, within the unique context of emerging markets. Therefore, a comprehensive understanding of stakeholder perspectives on AI-based services and adoption behavior is lacking, constraining banks' ability to align AI policies with market and regulatory requirements and fully realize the benefits of AI (Shi & Wang, 2025).

Modern banking institutions require an exclusive understanding of user behavior and perceptions to enable effective AI implementation in dynamic and less digitally mature environments. While earlier studies suggest that institutional and regulatory barriers can be addressed through technical capability development (Chung et al., 2023), failure to assess digital infrastructure, technological knowledge, skills, and perceptions of digitally enabled services leads to poor integration (Alnemer, 2022; Arjun et al., 2021; Boustani, 2022; Ionașcu et al., 2023). By examining how established adoption constructs operate under conditions of digital nativity and institutional immaturity, this study extends the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT2) by identifying their explanatory boundaries in AI-driven financial services. These models, renowned for their efficacy in explaining technology adoption, are particularly relevant for understanding complex user behaviors in novel contexts such as AI in banking, especially among a digital-native generation.

The focus on the Indonesian banking sector is guided by its rapid digital transformation and expanding Gen Z demographic, which offer a distinctive empirical setting. Indonesia represents a digitally evolving and rapidly transforming market, shaped by the rise of fintech firms, the Internet, and mobile banking, e-wallets, and peer-to-peer lending platforms (Affandi et al., 2024). This developmental stage, characterized by growing digital financial inclusion (Amaliah et al., 2024) and increasing Internet access among Gen Z (Global Findex, 2021), differs substantially from advanced digital economies. In this sense, the Indonesian banking context functions not only as an empirical setting but also as a theoretically informative environment for observing AI adoption, where rapid digital expansion coexists with uneven institutional maturity. This dynamic environment demands a deeper understanding of customer perceptions to enhance digital maturity and address societal integration challenges, underscoring the importance of examining AI adoption in Indonesian banks.

## HYPOTHESES DEVELOPMENT

The debate on the adoption of AI among digital banks continues to evolve because of dynamic business environments and individual-level factors. Prior research has examined organizational and individual adoption of AI using various theoretical models (Tamilmani et al., 2021); however, no single framework sufficiently captures the complexity of AI adoption in contemporary digital banking. Early technology acceptance research was shaped by models such as the theory of reasoned action (TRA) and the theory of planned behavior (TPB), which emphasized attitudes and subjective norms. Building on these foundations, the technology acceptance model (TAM) emerged as a seminal framework, focusing on perceived usefulness and perceived ease of use as key determinants of adoption (Davis, 1986). While the TAM has provided valuable insights into initial technology acceptance (Dwivedi et al., 2006; Williams et al., 2009), its parsimonious structure limits its ability to explain more complex adoption behaviors shaped by social and hedonic influences. As digital banking services increasingly rely on AI-enabled interactions, understanding adoption requires a framework that captures both foundational acceptance mechanisms and broader consumer-specific drivers. Accordingly, this study employs a combined TAM–utilization type analysis (UTAUT2) framework to investigate AI adoption and achieve its research objective of explaining how perceptions of AI-enabled banking services translate into adoption behavior among Generation Z (Gen Z).

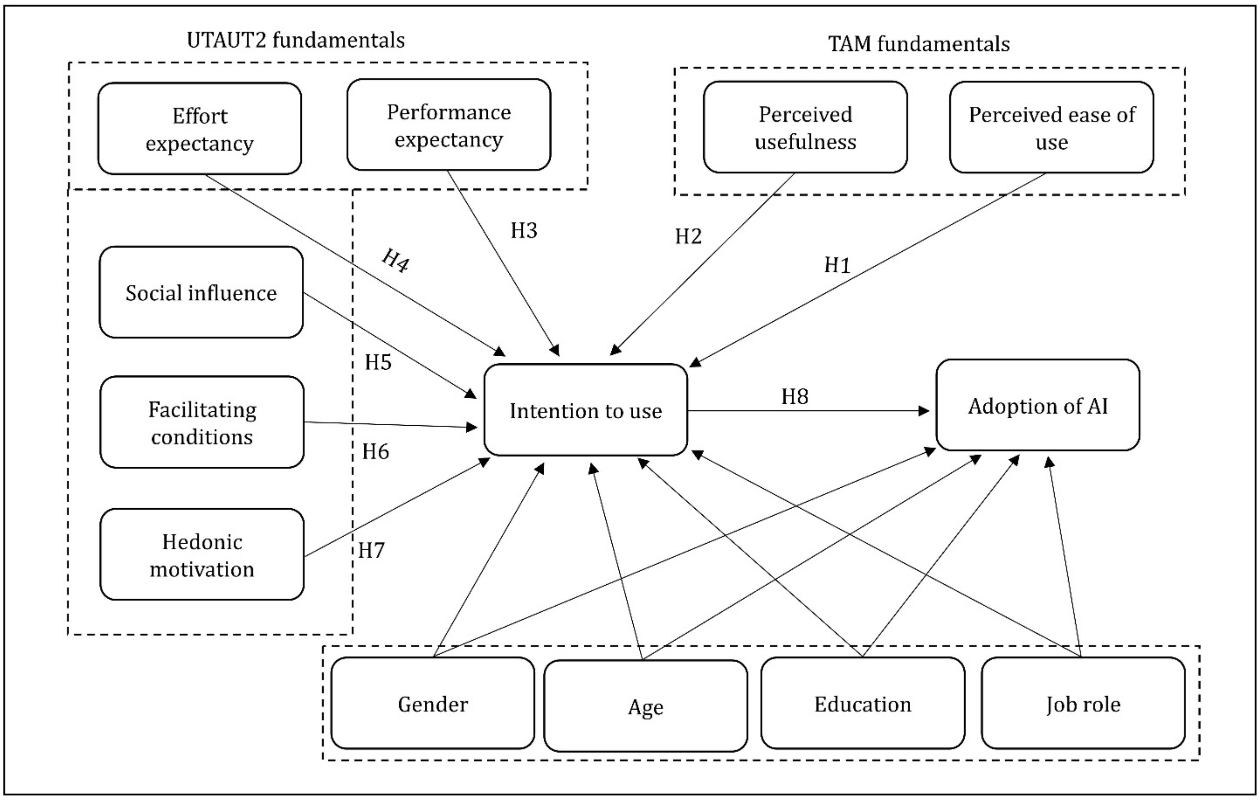


**Figure 1**
**Conceptual framework**

The integrated use of TAM and UTAUT2 is particularly appropriate and novel in this research context. UTAUT and its extension, UTAUT2, were developed to address the limitations of earlier models by incorporating a broader set of influencing factors, including social influence, facilitating conditions, hedonic motivation, price value, and habit (Venkatesh et al., 2012). UTAUT2 has emerged as a widely applied model in studies of individual and organizational adoption of digital technologies, particularly in consumer-oriented contexts (Papathomas et al., 2025; Tamilmani et al., 2021). However, its comprehensive nature can obscure the fundamental drivers of initial acceptance, which remain central to early-stage adoption decisions. Conversely, TAM's continued relevance lies in its strong explanatory power for understanding how perceived usefulness and perceived ease of use shape initial adoption intentions (Noreen et al., 2023; Nouraldeen, 2023). Therefore, integrating TAM with UTAUT2 allows this study to balance conceptual clarity with explanatory richness. This combined framework enables a nuanced examination of Gen Z's adoption behavior by capturing both basic acceptance mechanisms and consumer-specific motivations that are particularly salient for a digital-native generation interacting with novel technologies such as AI in banking. By applying this integrated approach to Gen Z in Indonesia's digital-banking sector, this study tests the contextual relevance and boundaries of both models, contributing to their theoretical refinement in emerging markets.

Building on the foundational TAM model, perceived ease of use (PEOU) remains a critical determinant in the technology adoption literature, particularly for novel systems such as AI in banking. Davis (1986) established PEOU as the degree to which an individual believes that using a particular system is effortless. In the context of AI, studies consistently show that technologies requiring low cognitive and intuitive skills are more readily adopted, especially when seeking complex services (Byambaa et al., 2025; Shaikh & Karjaluoto, 2015). This suggests that for Gen Z, who are accustomed to seamless digital interactions, the intuitiveness and simplicity of AI-enabled banking interfaces are paramount in shaping their initial acceptance and sustained use. The ease of interaction in AI-enabled digital banks refers to a user interface designed to simplify users' interactions while seeking complex banking services. It is posited that an interactive AI system requiring low cognitive and mental effort may positively shape users' perceptions and lead to its adoption. Recent empirical studies have confirmed that factors such as the possibility of unintentional errors, clarity of instruction, dedicated time and resources, and the extent of mental and physical effort may influence users' PEOU of modern digital technologies (Manrai et al., 2021; Papathomas et al., 2025). Accordingly, the first research hypothesis (H1) is as follows:
H1: PEOU affects the intention to use AI in digital banking.

Another key feature of TAM is its ability to predict behavioral intentions and the adoption of users based on the perceived usefulness (PU) of innovative systems. Both PU and PEOU account for approximately 40% of the changes in behavioral intentions and are frequently employed to investigate the adoption or rejection of digital financial technologies (Noreen et al., 2023). PU refers to the expected usefulness of technology in enhancing work efficiency while performing routine tasks (Davis, 1986). Recent studies have described PU as a positive driver of technology adoption in small and large firms because of its usefulness in optimizing the work efficiency of employees in these firms (Manrai et al., 2021). In the theoretical framework of this study, PU refers to customers' perceptions of AI's capabilities to resolve banking issues and enhance their banking experience (Bilal et al., 2024; Fares et al., 2023). Past studies have confirmed that easy-to-use technologies are perceived as effective in improving performance and gaining financial benefits for customers; hence, they have higher adoption rates (Rahman et al., 2023). Following these arguments, our second hypothesis (H2) is proposed as follows:
H2: PU affects the intention to use AI in digital banking.

Both the original UTAUT and advanced UTAUT2 models document the significance of performance expectancy (PE) in the adoption of digital technologies (Tamilmani et al., 2021). PE broadly measures the expected benefits of using desired technologies and their influence on users' work efficiency. Often, adoption decisions are guided by sustainable performance orientation rather than short-term benefits from new technologies (Venkatesh et al., 2012). These extended changes due to technology adoption decisions and their impact on work performance are better measured by PE instead of PU, which focuses on the temporary rewards of technology. The adoption of modern technologies by digital banks also highlights their significance in improving operational, financial, and sustainability performance, reinforcing that the adoption of AI may create long-term benefits (Ali et al., 2023; Mei et al., 2024; Papathomas et al., 2025). The third hypothesis (H3) of this study is as follows:
H3: PE affects the intention to use AI in digital banking.

Venkatesh et al. (2012) envisaged effort expectancy (EE) as the level of ease experienced while interacting with certain technologies and systems. Thematic management and social science scholars

have shown keen interest in evaluating the perceptions of the effectiveness and efficiency of different technologies. From a conceptual perspective, EE evaluates the simplicity and intuitiveness of interacting with AI-powered services, known as virtual financial assistants and/or automated loan processing (Suhartanto et al., 2022). Therefore, a user-friendly and seamless experience creates a positive attitude towards AI-powered services (Agarwal et al., 2025; Lin & Lee, 2024; Tulcanaza-Prieto et al., 2023). Davis's (1986) TAM and Venkatesh et al.'s (2012) UTAUT2 attribute effort perception (EP) as a direct predictor of behavioral intention to adopt innovative systems. Therefore, reducing perceptual complexities, such as overcoming personal and organizational barriers, is critical to improving AI in digital banks (Rahman et al., 2023). Following the newness of AI in Indonesian digital banks, it can be inferred that certain complexities may arise during its adoption due to the gaps between the expected input and the actual output obtained by users (Suhartanto et al., 2022; Indriasari et al., 2019). Some companies may find AI simple and easy to adopt, while others may perceive it as complicated. These underlying differences led to the establishment of Hypothesis 4 (H4).
H4: EP affects the intention to use AI in digital banking.

Social influence (SI) is defined as the extent to which an individual perceives that others believe he or she should use a technology. SI is a key construct of UTAUT2 (Venkatesh et al., 2012). Although many studies have confirmed its prevalence in shaping technology adoption (Mei et al., 2024; Papathomas et al., 2025), its impact can vary significantly depending on the cultural context and specific technology. For digital natives such as Gen Z, who are often characterized by independent decision-making and a strong personal identity, the influence of social pressure on AI adoption in banking may differ from previous findings, warranting a specific investigation in this context. Hence, we hypothesize;
H5: SI affects the intention to use AI in digital banking.

UTAUT2 recommends establishing facilitating conditions (FC) to simplify the execution of tasks using new technologies (Venkatesh et al., 2012). FC refers to dedicated resources and support that facilitate the performance of an act. Recent studies investigating the digital transformation journey of firms operating in dynamic business environments have revealed that FC positively affects the intention to adopt seamless technologies across all levels (Noreen et al., 2023). The FC for developing AI systems in digital banks includes readily available customer support, reliable AI systems, and dedicated infrastructure to support digital banking (Candiwan & Annikmah, 2024; Rahman et al., 2023). Accordingly, the sixth hypothesis (H6) is as follows:
H6: FC affects the intention to use AI in digital banking.

Another novel construct of UTAUT2 is hedonic motivation (HM), which indicates a positive bond between a new technology or system and its potential users (Venkatesh et al., 2012). HM is associated with the joy and happiness experienced while using new technologies, surpassing the underlying functional benefits. The academic literature reveals mixed effects of HM on technology adoption. Some studies have criticized overwhelming joy for compromising basic service standards, while others have described it as a positive enabler of innovation adoption (Tulcanaza-Prieto et al., 2023). This study conceptualizes HM to examine the anticipated emotions while interacting with AI systems and how these emotions influence users' intentions and adoption. This study endeavors to explore the impact of AI in overcoming digital banking users' AI dilemmas, ranging from basic banking issues to advanced and complex affairs (Byambaa et al., 2025). The seventh hypothesis (H7) is as follows:
H7: HM affects the intention to use AI in digital banking.

Individuals' readiness to exhibit certain behaviors is determined by their behavioral intentions, also referred to as intention to use (ITU). Davis (1986) and Venkatesh et al. 's (2007, 2012) seminal studies suggest that ITU serves as a bridge between users' perceptions, expectations, and beliefs and the

adoption of technologies. The emerging literature discussing the diffusion of modern digital technologies at the organizational and individual levels highlights the capabilities of ITU and the adoption of digital technologies and systems (Tamilmani et al., 2021). The theoretical orientation of this study postulates that Gen Z's perceptions of AI are affected by factors such as perceived ease of use, perceived usefulness, performance and effort expectancies, social and facilitating conditions, and hedonic motivations. Hence, the eighth hypothesis (H8) is as follows:
H8: ITU affects the adoption of AI in digital banking.

To enhance the robustness of our model and account for potential demographic influences on technology adoption, we included gender (GEN), age (AGE), education (EDU), and job role (JL) as control variables. Prior research suggests that these factors can moderate technology acceptance (Alghamdi et al., 2025; Nouraldeen, 2023). Specifically, education level and job role may influence an individual's exposure to, understanding of, and need for advanced technologies such as AI, whereas age and gender might reflect differing digital literacy levels or risk perceptions within the Gen Z demographic. Controlling for these variables allowed for a clearer assessment of the direct effects of our primary theoretical constructs.

## METHOD

This study employed a cross-sectional survey design to achieve its research objectives. The survey measures for the constructs were adapted from the established literature on technology adoption (Davis, 1986; Lin & Lee, 2024; Mei et al., 2024; Noreen et al., 2023; Papathomas et al., 2025; Tulcanaza-Prieto et al., 2023; Venkatesh et al., 2007, 2012). The questionnaire was pretested by seven experts (four academics and three practitioners) to ensure clarity and validity prior to finalization. The experts possessed formal and practical knowledge regarding the cognitive and personal factors that may influence users' AI adoption behavior. Consequently, their feedback was crucial in selecting the relevant indicators during the development of our research instrument. We targeted the digital banking users located in Bandung City (West Java) of Indonesia and fulfilled the Gen Z demographic (born after 1997 and aged above 18 years) criteria. Sampling was done using purposive sampling to ensure that respondents met these specific demographic and user requirements.

The respondents provided written informed consent before participating in this study. The questionnaire comprised two sections. Section A covered the demographic details of the respondents, including gender, age, education level, and job role. The main content evaluating the factors influencing the adoption of AI is covered in section B. We used 26 items to explore Gen Z's perceptions of AI and the impact of these perceptions on their adoption behavior. The discussion presented in the analytical framework of this study highlighted that perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation related to AI may influence adoption. The questionnaire items for each construct (AI, ITU, PEOU, PU, PE, EE, SI, FC, HM) were adapted from established literature, including Alalwan et al. (2017), Belanche et al. (2019), Davis (1986), Indriasari et al. (2019), Papathomas et al. (2025), Venkatesh et al. (2003), and Venkatesh et al. (2012). A detailed breakdown of the measurement items and their sources is presented in Table 1. To capture responses to each item, respondents were provided with a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Data were collected through an online survey distributed between December 15, 2024, and January 30, 2025. Of the 618 surveys distributed, 427 were completed, yielding a response rate of 69.09%. After excluding 11 surveys with incomplete information, 416 valid responses were used for analysis, exceeding the typical sample size recommendations for this type of study. Additional information on the respondents' demographics is presented in Table 1.

**Table 1.**
**Survey questionnaire**

| Variables | Source | Items | Estimates | Mean scores |
|---|---|---|---|---|
| Adoption of AI (AI) | Papathomas et al. (2025) | AI1<br>AI2<br>AI3 | I frequently use AI to manage my banking affairs.<br>I rely on AI for certain banking transactions.<br>I encourage others to use AI. | 4.22 |
| Intention to use (ITU) | Davis (1986) | ITU1<br>ITU2<br>ITU3 | I intend to use AI in the future.<br>It is likely that I may use AI in the future.<br>I will frequently use AI in the future. | |
| Perceived ease of use (PEOU) | Belanche et al. (2019) | PEOU1<br>PEOU2<br>PEOU3 | I can interact with AI better than human interaction.<br>I can interact with AI provided humanistic support is available.<br>My interaction with AI is not limited by place and time. | 4.18 |
| Perceived usefulness (PU) | Davis (1986) | PU1<br>PU2 | AI will understand the questions I pose.<br>AI will give me a reasonable explanation of the queries I make. | 3.87 |
| Performance expectancy (PE) | Venkatesh et al. (2003) | PE1<br>PE2<br>PE3 | AI will allow me to complete my banking affairs.<br>AI is most likely to offer me a solution to important issues.<br>AI will improve my work efficiency. | 4.55 |
| Effort expectancy (EE) | Venkatesh et al. (2003) | EE1<br>EE2<br>EE3 | AI will generate clear information.<br>AI will produce sufficient information.<br>AI will provide me with error-free information. | 4.40 |
| Social influence (SI) | Alalwan et al. (2017) | SI1<br>SI2<br>SI3 | I may use AI to coordinate banking functions following the influence of people who often inspire me.<br>I may use AI to coordinate banking functions following the influence of people important to me.<br>I may use AI to coordinate banking functions following the influence of people whose opinions are valuable to me. | 3.51 |
| Facilitating conditions (FC) | Indriasari et al. (2019) | FC1<br>FC2<br>FC3<br>FC4 | I have the preliminary knowledge essential for interacting with AI.<br>I have access to the technological infrastructure essential for interacting with AI.<br>Interacting with AI will be simple and easy.<br>The mandatory AI skills and knowledge are easy to acquire. | 3.28 |
| Hedonic motivation (HM) | Venkatesh et al. (2012) | HM1<br>HM2 | I will be keen on using AI.<br>I will be frustrated by using AI. | 4.78 |

**Table 2.**
**Demographic profiles of respondents**

| Demographics | Items | Frequencies | Percentage |
|---|---|---|---|
| | Male | 223 | 53.60 |
| Gender | Female | 193 | 46.39 |
| | Total | 416 | 100 |
| | Below 18 | 104 | 25.00 |
| | Between 19-25 | 231 | 55.52 |
| Age (years) | Above 26 | 81 | 19.47 |
| | Total | 416 | 100 |
| | Diploma/certificate | 67 | 16.10 |
| | Bachelor | 226 | 54.32 |
| Education level | Master | 123 | 29.56 |
| | Total | 416 | 100 |
| | University students | 168 | 40.38 |
| | Private sector | 129 | 31.00 |
| Job role | Government employee | 119 | 28.60 |
| | Total | 416 | 100 |

Given the exploratory nature of this study and its focus on predicting behavioral intentions, the analytical framework (Figure 1) was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). This approach is particularly suitable for complex models when the research aims to predict dependent variables (Hair Jr. et al., 2017).

The correlation between the latent variables was estimated using Pearson's correlation test. Discriminant validity was also established, as evidenced by the square root of the AVE for each construct being greater than its correlation with other constructs (Fornell & Larcker criterion), as detailed in Table 3.

**Table 3.**
**Correlation matrix**

| Constructs | AI | ITU | PEOU | PU | PE | EE | SI | FC | HM |
|---|---|---|---|---|---|---|---|---|---|
| AI | 0.552 | | | | | | | | |
| ITU | 0.145 | 0.693 | | | | | | | |
| PEOU | 0.321 | 0.375 | 0.731 | | | | | | |
| PU | 0.184 | 0.220 | 0.317 | 0.658 | | | | | |
| PE | 0.114 | 0.210 | -0.127 | 0.219 | 0.703 | | | | |
| EE | 0.284 | 0.098 | 0.068 | 0.036 | 0.041 | 0.728 | | | |
| SI | 0.138 | 0.085 | 0.121 | 0.112 | 0.117 | 0.150 | 0.740 | | |
| FC | 0.038 | 0.010 | 0.014 | 0.034 | 0.048 | 0.059 | 0.055 | 0.703 | |
| HM | 0.168 | 0.095 | 0.081 | 0.147 | 0.134 | 0.128 | 0.094 | 0.105 | 0.803 |

Survey-based studies may exhibit common method bias (CMB) issues, which are generally addressed by using several items to measure each construct. We followed Kock's (2015) technique and requested respondents to complete the questionnaire in accordance with the formally established AI policies of their companies, instead of using personal experiences while interacting with digital governance technologies. Next, we estimated the CMB by performing Harman's single-factor test and evaluated the results. Harman's single-factor test indicated that common method bias was not a significant concern, with a single factor accounting for less than 50% of the total variance (42.83%).

The endogeneity of exogenous variables is another major concern in empirical studies. To address this issue, we referred to the literature review and conceptualized the adoption of AI as an exogenous variable and assumed that perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and intention to use are indicators of AI and endogenous variables, indicating that endogeneity will not affect our findings. Additionally, the Durbin-Wu-Hausman test was performed by regressing these indicators with AI, and their residuals were used as regressors to verify the hypothetical linkage. The results of the parameter estimates were statistically insignificant, confirming our conceptual underpinnings.

The quality and validity of the measurement model were estimated by analyzing the coefficient values of scale composite reliability (SCR), Cronbach's alpha, and average variance extracted (AVE). The findings of the measurement model's quality showed that all constructs demonstrated satisfactory internal consistency, with SCR and Cronbach's alpha coefficients exceeding the recommended threshold of 0.70 (Hair Jr. et al., 2017). It was also confirmed that the latent constructs adequately explained the variance in their respective items, with AVE values indicating sufficient convergent validity (Table 4).

**Table 4.**
**The reliability statistics of items and factor loadings**

| Variables | Items | Factor loadings | Variance | Error | SCR | AVE |
|---|---|---|---|---|---|---|
| AI | AI1 | 0.853 | 0.860 | 0.721 | 0.88 | 0.77 |
| | AI2 | 0.834 | 0.854 | 0.783 | | |
| | AI3 | 0.785 | 0.816 | 0.825 | | |
| ITU | ITU1 | 0.768 | 0.786 | 0.666 | 0.79 | 0.74 |
| | ITU2 | 0.839 | 0.874 | 0.657 | | |
| | ITU3 | 0.710 | 0.756 | 0.718 | | |
| PEOU | PEOU1 | 0.734 | 0.793 | 0.749 | 0.84 | 0.80 |
| | PEOU2 | 0.796 | 0.828 | 0.676 | | |
| | PEOU3 | 0.756 | 0.761 | 0.617 | | |
| PU | PU1 | 0.902 | 0.949 | 0.875 | 0.76 | 0.72 |
| | PU2 | 0.827 | 0.881 | 0.826 | | |
| PE | PE1 | 0.883 | 0.925 | 0.856 | 0.79 | 0.77 |
| | PE2 | 0.815 | 0.876 | 0.664 | | |
| | PE3 | 0.796 | 0.802 | 0.683 | | |
| EE | EE1 | 0.924 | 0.946 | 0.692 | 0.81 | 0.78 |
| | EE2 | 0.892 | 0.908 | 0.653 | | |
| | EE3 | 0.761 | 0.769 | 0.660 | | |
| SI | SI1 | 0.846 | 0.883 | 0.608 | 0.85 | 0.80 |
| | SI2 | 0.727 | 0.745 | 0.759 | | |
| | SI3 | 0.758 | 0.786 | 0.806 | | |
| FC | FC1 | 0.788 | 0.797 | 0.785 | 0.78 | 0.71 |
| | FC2 | 0.864 | 0.925 | 0.846 | | |
| | FC3 | 0.807 | 0.837 | 0.855 | | |
| | FC4 | 0.823 | 0.864 | 0.767 | | |
| HM | HM1 | 0.916 | 0.959 | 0.734 | 0.88 | 0.81 |
| | HM2 | 0.892 | 0.900 | 0.669 | | |

# RESULTS AND DISCUSSION

## Results

**Table 5.**
**Results and summary of structural paths**

| Hypothesis | Effect of | On | β | ρ | Decision criteria |
|---|---|---|---|---|---|
| H1 | PEOU | ITU | 0.135 | < 0.001 | Supported |
| H2 | PU | ITU | 0.206 | < 0.001 | Supported |
| H3 | PE | ITU | 0.331 | < 0.001 | Supported |
| H4 | EE | ITU | 0.278 | < 0.001 | Supported |
| H5 | SI | ITU | 0.098 | > 0.001 | Not supported |
| H6 | FC | ITU | 0.016 | > 0.001 | Not supported |
| H7 | HM | ITU | 0.342 | < 0.001 | Supported |
| H8 | ITU | AI | 0.319 | < 0.001 | Supported |
| *CVs* | | | | | |
| | GEN | ITU | 0.058 | > 0.001 | Not supported |
| | GEN | AI | 0.044 | > 0.001 | Not supported |
| | AGE | ITU | 0.053 | > 0.001 | Not supported |
| | AGE | AI | 0.037 | > 0.001 | Not supported |
| | EDU | ITU | 0.126 | < 0.001 | Supported |
| | EDU | AI | 0.203 | < 0.001 | Supported |
| | JR | ITU | 0.185 | < 0.001 | Supported |
| | JR | AI | 0.262 | < 0.001 | Supported |
| Constructs | $R^2$ | $f^2$ | $Q^2$ | | |
| ITU | 0.303 | 0.323 | 0.341 | | |
| PEOU | 0.282 | 0.308 | 0.318 | | |
| PU | 0.255 | 0.281 | 0.310 | | |
| PE | 0.340 | 0.370 | 0.385 | | |
| EE | 0.346 | 0.386 | 0.391 | | |
| SI | 0.012 | 0.013 | 0.017 | | |
| FC | 0.017 | 0.019 | 0.020 | | |
| HM | 0.419 | 0.425 | 0.438 | | |
| *CVs* | | | | | |
| GEN | 0.003 | 0.009 | 0.014 | | |
| AGE | 0.006 | 0.010 | 0.017 | | |
| EDU | 0.380 | 0.391 | 0.398 | | |
| JR | 0.169 | 0.180 | 0.194 | | |

The research hypotheses were tested by estimating the standard errors and significance levels of the latent constructs using the PLS-based bootstrapping approach. This technique is useful for measuring parameter estimates and is effective in assuming a multivariate' normal distribution (Hensler et al., 2014). The results of the PLS output show that $R^2 = 0.568$, establishing that PEOU, PU, PE, EE, SI, FC, HM, ITU, and CVs explain a significant variance in AI. The hypothetical relationship between latent variables was analyzed by reviewing the coefficient of standardized β and the significance (ρ) level. The PLS estimates (Table 5) revealed significant positive effects for several hypotheses. Specifically, H1 (PEOU → ITU, β = 0.135; ρ = < 0.001), H2 (PU → ITU, β = 0.206; ρ < 0.001), H3 (PE → ITU, β = 0.331; ρ = < 0.001), and H4 (EE → ITU, β = 0.278; ρ < 0.001) were all supported, indicating that perceived ease of use, perceived usefulness, performance expectancy, and effort expectancy positively influence the intention to use AI. Conversely, H5 (SI → ITU, $\beta = 0.098$; $\rho > 0.001$) and H6 (FC → ITU, $\beta = 0.016$; $\rho > 0.001$) were not supported, suggesting that social influence and facilitating conditions do not significantly impact Gen Z's intention to use AI in this context. Hedonic motivation (H7: HM → ITU, $\beta = 0.342$, $\rho < 0.001$) also significantly influenced the intention to use AI banking. Finally, intention to use (H8: ITU → AI, $\beta = 0.319$, $\rho < 0.001$) was a significant predictor of AI adoption. The CVs for gender and age were insignificant moderators of ITU/AI adoption (Table 5). In contrast, education level ($\beta = 0.126/0.203$, $\rho < 0.001$) and job role ($\beta = 0.185/0.262$, $\rho < 0.001$) emerged as significant moderators, influencing Gen Z's AI adoption behavior.

The PLS path coefficients were obtained by running 500 bootstraps to analyze standardized β and their ρ values (Table 5). The explanatory power of the theoretical model was explored by analyzing the variance explained ($R^2$) of the exogenous variables. The theoretical model demonstrated substantial explanatory power for AI adoption, with an $R^2$ of 0.568. Table 5 presents the $R^2$ values of the individual exogenous variables.

To estimate the effect size of the latent variables, we followed Cohen’s $f^2$ technique to classify effects into large (0.35), medium (0.15), and small (0.02) ranges (Cohen, 1998). Cohen’s $f^2$ technique classified the effect sizes of the latent variables and showed that PE, EE, HM, and EDU exhibited strong effects on AI adoption. PEOU, PU, ITU, and JR showed moderate effects, whereas SI, FC, GEN, and AGE had weak effects. In addition, Stone-Geisser’s $Q^2$ values for all endogenous variables were above zero, confirming the theoretical model's acceptable predictive relevance (Table 5).

## Discussion

The empirical analysis reveals a nuanced pattern of AI adoption among Gen Z users of Indonesian digital banking applications. The findings indicate that intrinsic motivations, including perceived ease of use, perceived usefulness, performance expectancy, effort expectancy, and hedonic motivation, are the primary drivers of adoption intentions. In contrast, traditional external influences, such as social influence and facilitating conditions, as well as demographic characteristics such as gender and age, exhibit limited explanatory power. This pattern suggests a distinct behavioral profile for Gen Z in emerging digital contexts and aligns with recent studies emphasizing the growing role of AI in digital banking operations (Agarwal et al., 2025; Ali et al., 2023; Noreen et al., 2023; Papathomas et al., 2025). Consistent with prior evidence, Gen Z users demonstrate positive intentions toward AI adoption, which are shaped predominantly by individual-level perceptions rather than external pressures (Indriasari et al., 2019; Rahman et al., 2023; Suhartanto et al., 2022). Collectively, these findings extend the integrated TAM–UTAUT2 framework by illustrating how the salience of established constructs shifts when applied to a digitally native population in an emerging economy.

The strong support for H1 (PEOU→ITU) underscores the centrality of intuitive and user-friendly AI interfaces for Indonesian Gen Z, accustomed to seamless digital interactions and perceive AI-enabled banking services as offering superior accessibility and convenience compared to traditional human interaction. This preference reflects their inclination toward self-service and anytime, anywhere access within a rapidly digitalizing banking environment. This finding is consistent with earlier studies suggesting that technologies requiring low cognitive effort are more readily adopted for complex service interactions (Byambaa et al., 2025; Shaikh & Karjaluoto, 2015). Accordingly, banks seeking to enhance AI adoption should prioritize interface simplicity, clear instructions, and user-centered design to strengthen perceptions of ease of use (Manrai et al., 2021; Papathomas et al., 2025). Similarly, support for H2 (PU → ITU) confirms that AI adoption is reinforced when users perceive AI to improve their understanding of financial services through clear and detailed explanations. This aligns with prior research highlighting the importance of perceived usefulness in optimizing performance and resolving banking-related issues in digital environments (Bilal et al., 2024; Mei et al., 2024; Noreen et al., 2023).

The significant influence of performance expectancy (H3) suggests that Indonesian Gen Z views AI as a comprehensive solution capable of supporting a wide range of banking activities, from routine transactions to personalized financial advice. This perception reflects high digital literacy and strong expectations of efficiency, reinforcing the readiness to embrace AI-driven financial services. This finding is consistent with earlier studies emphasizing the role of advanced digital technologies in delivering economic, social, and financial benefits (Kanellopoulou et al., 2025; Lee & Chen, 2022; Venkatesh et al., 2012). In addition, support for H4 indicates that effort expectancy is not a barrier to AI adoption. Contrary to concerns regarding the inaccurate or insufficient information generated by digital technologies, Gen Z users appear confident in AI's capacity to provide reliable support in sensitive financial contexts. This reinforces the claim that AI-enabled services can enhance the customer experience through virtual assistance while contributing to institutional legitimacy and system stability (Lin & Lee, 2024; Noreen et al., 2023).

In contrast, the rejection of H5 challenges conventional assumptions regarding the role of social influence in technology adoption. While prior studies emphasize the importance of peer and societal pressures (Venkatesh et al., 2012), the present findings suggest that Indonesian Gen Z adoption decisions are primarily guided by personal utility rather than external validation (Suhartanto et al., 2022). This divergence highlights a theoretical boundary for the applicability of social influence within UTAUT2 when applied to highly digitalized and self-directed user groups. Similarly, the nonsignificant effect of facilitating conditions (H6) diverges from earlier findings that emphasize infrastructure and support as key enablers (Candiwan & Annikmah, 2024; Rahman et al., 2023). For digitally literate Gen Z users, foundational infrastructure and preliminary knowledge may be taken for granted, rendering these factors less salient. This observation aligns with evidence suggesting that effective engagement with advanced technologies requires capabilities beyond those of conventional facilitators (Hartanto et al., 2021). Together, the non-significance of social influence and facilitating conditions underscores important boundary conditions for UTAUT2 in digitally mature cohorts in emerging markets.

These results further confirm the importance of hedonic motivation in shaping AI adoption behavior. Consistent with prior studies, positive emotional engagement with technology fosters stronger user–system bonds, reinforcing adoption intention (Byambaa et al., 2025; Tulcanaza-Prieto et al., 2023). Finally, strong support for H8 (ITU → AI adoption) reaffirms the central role of behavioral intention as the most proximate predictor of adoption, consistent with TAM and UTAUT2 (Davis, 1986; Tamilmani et al., 2021; Venkatesh et al., 2007, 2012). The results of the CVs, operationalized as demographic moderators, revealed interesting findings. The insignificance of gender and age as moderators of AI adoption within the Gen Z cohort is a critical finding that challenges several established studies (Alghamdi et al., 2025; Nouraldeen, 2023). This suggests that among digital natives in Indonesia, the shared experience of growing up with pervasive digital technology may homogenize their approach to AI adoption, diminishing the traditional influence of these demographic variables on AI adoption. This implies a generational shift in which digital fluency and exposure outweigh gender or age-related differences in technology acceptance, offering a novel perspective on demographic moderating effects within TAM and UTAUT2 for specific, digitally-immersed populations.

## CONCLUSION

This study investigated the behavioral indicators influencing Generation Z's adoption of artificial intelligence in Indonesia's digital banking sector by integrating the UTAUT2 and TAM models. Our findings confirm that intrinsic motivations, namely, perceived ease of use, usefulness, performance expectancy, effort expectancy, and hedonic motivation, significantly drive AI adoption. Notably, external factors such as social influence and facilitating conditions, as well as demographic variables such as gender and age, were found to be insignificant. Conversely, the level of education and job role emerged as significant moderators.

This study refines the integrated TAM and UTAUT2 frameworks by demonstrating how the unique characteristics of Gen Z in an emerging digital economy reshape the influence of external factors. It highlights the boundary conditions for the applicability of social influence and facilitating conditions in highly digitally literate populations, thereby challenging assumptions from studies in more developed markets.

In practice, our findings offer critical guidance to Indonesian regulatory bodies, such as the Otoritas Jasa Keuangan. The diminished role of social influence and facilitating conditions suggests that regulatory efforts should focus less on broad societal campaigns or generic infrastructure provisions and more on ensuring the intrinsic value and seamless functionality of AI services. Policies should incentivize banks to enhance perceived usefulness and ease of use, aligning with Gen Z's self-directed adoption patterns, thereby fostering more effective societal integration of digital banking and maximizing its contribution to economic development. Regulators responsible for controlling and regulating the performance of the financial sector are also encouraged to modify their existing digital policies to make legal exceptions, such as licensing discounts, tax levies, and annual rebates for digital firms seeking to adopt AI, achieve societal integration, and improve digital financial inclusion in the country. Financial consultants may use our findings to propose inclusive digital marketing strategies to attract a potentially profitable segment of the market, described as Gen Z in this study.

The cross-sectional survey design and sampling of Gen Z from a single Indonesian city limit the findings of this study. Future research could explore the long-term effects of AI adoption through longitudinal studies, investigate the specific 'technology aspects' that influence users' perceptions, and employ mixed methodological approaches to provide richer qualitative insights into Gen Z's intrinsic motivations. Further examination of the diminished role of social influence in other digitally native cohorts or emerging markets would also be valuable.

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