International Journal of Information Management Data Insights 5 (2025) 100371

Contents lists available at ScienceDirect

International Journal of Information Management Data Insights

journal homepage: www.elsevier.com/locate/jjimei

Determinants of artificial intelligence adoption in the financial services industry: Understanding employees' perspectives

Ahyar Yuniawan [a,*], Hersugondo Hersugondo [a], Fuad Mas'ud [a], Hengky Latan [b], Douglas W.S. Renwick [c]

[a] Diponegoro University, Jl. Prof. Sudarto, S.H. No.13 Semarang, 50275, Indonesia
[b] HLC Consulting, Jl. Kertanegara Selatan V No 5B Semarang, 50241, Indonesia
[c] Nottingham Business School, 50 Shakespeare Street, Nottingham, UK

ARTICLE INFO

Keywords:
Artificial intelligence
Levels of knowledge and awareness
Perceived risks and benefits
Self-confidence
Managerial support
Intention to use AI

ABSTRACT

This study examines the factors influencing AI adoption in Indonesia's financial services sector, focusing on knowledge and awareness levels, perceived risks and benefits, self-confidence, and the moderating role of managerial support. Grounded in innovation diffusion theory (IDT), protection motivation theory (PMT), and self-determination theory (SDT), the study analyzes data from 489 employees using structural equation modeling with SmartPLS 4 software to test the hypotheses. The findings reveal that higher levels of knowledge and awareness, along with self-confidence, positively influence AI adoption intentions, while perceived risks and benefits exert a negative effect. Furthermore, managerial support moderates these relationships by enhancing the positive effects of knowledge and awareness levels and self-confidence, while mitigating the negative impact of perceived risks. These results emphasize the critical role of managerial support in promoting AI adoption and highlight the necessity of cultivating a supportive organizational culture and leadership to ensure successful AI integration.

1. Introduction

The integration of Artificial Intelligence (AI) into the financial services industry offers transformative potential, particularly in enhancing efficiency, decision-making, and customer service (Liu et al., 2024; Norzelan et al., 2024; Shamim et al., 2023). In Indonesia, the financial sector is at a pivotal moment, where adopting AI could lead to significant improvements in operational processes and service delivery. However, for financial institutions to fully capitalize on AI capabilities, it is essential to understand the factors that influence the intention to adopt these technologies (Armutcu et al., 2024; Li et al., 2024; Norzelan et al., 2024).

Much of the existing literature on AI adoption focuses on developed markets (Barile, Secundo, & Bussoli, 2024; Hussain et al., 2024; Liu et al., 2024; Pham et al., 2024), where technological infrastructure and regulatory environments are more advanced. However, these studies often fail to capture the unique challenges faced by emerging economies like Indonesia, which contends with fragmented technology adoption, inconsistent digital literacy, and insufficient regulatory guidelines for AI implementation (Veglianti et al., 2022; Yang et al., 2024; Zhang et al., 2023). Moreover, financial institutions in Indonesia face additional barriers, such as concerns over data privacy, cybersecurity, and ethical AI usage, while also needing to address the diverse socioeconomic backgrounds of their customers. Tailored approaches are necessary to ensure inclusivity and accessibility in AI integration. Compounding these challenges is the lack of empirical studies in Indonesia that explore how levels of knowledge and awareness influence AI adoption intentions, leaving a significant research gap in understanding context-specific adoption dynamics (Armutcu et al., 2024; Barile et al., 2024; Yang et al., 2024).

In addition to knowledge and awareness, the perceived risks and benefits of AI are critical determinants of adoption (Rana et al., 2022; Schiavo et al., 2024). While AI offers substantial advantages, such as enhanced efficiency and improved customer experiences, concerns about data privacy, security, and potential job displacement pose significant barriers to adoption (Cao et al., 2023; Shuqair et al., 2024).

* Corresponding author.
E-mail addresses: ahyar_y@live.undip.ac.id (A. Yuniawan), hersugondo@live.undip.ac.id (H. Hersugondo), fuad.mas'ud@live.undip.ac.id (F. Mas'ud), latanhengky@gmail.com (H. Latan), douglas.renwick@ntu.ac.uk (D.W.S. Renwick).

https://doi.org/10.1016/j.jjimei.2025.100371

Current studies have not sufficiently examined how these risk perceptions balance against perceived benefits. This lack of understanding hinders the development of targeted interventions aimed at mitigating employee fears and emphasizing the positive impacts of AI (Rana et al., 2022; Schiavo et al., 2024).

Furthermore, the level of self-confidence in using AI technologies is another pivotal factor affecting the intention to use. This confidence stems from both individual technological proficiency and the organizational readiness to integrate and manage AI systems effectively (Al-Sharafi et al., 2023; Iyer & Bright, 2024). Variations in educational background, exposure to technology, and organizational culture significantly affect how self-confidence influences AI adoption. Understanding these dynamics can help identify both the obstacles and enablers of AI integration, thereby providing a foundation for targeted interventions to build user confidence (Kim et al., 2024; Schiavo et al., 2024).

Beyond individual factors, managerial support plays a pivotal role in moderating the relationships between these elements and the intention to adopt AI (Chen et al., 2021). Strong leadership and organizational backing are vital for successful AI adoption, as they create a supportive environment that mitigates risks and enhances employee readiness (Chen et al., 2021; Li et al., 2019). Managers must clearly articulate the benefits of AI, align its integration with organizational goals, and provide employees with access to training, hands-on experience, and support systems. Additionally, addressing perceived risks requires robust data security measures and ethical guidelines to build a trustworthy environment. By combining strategic leadership with comprehensive support systems, managerial actions can foster confidence and reduce resistance, ultimately facilitating smoother AI integration into Indonesia's financial sector (Bankins & Formosa, 2023; Shuqair et al., 2024).

This study aims to examine how levels of knowledge and awareness, perceived risks and benefits, and self-confidence influence the intention to adopt AI in Indonesia's financial services industry, with managerial support as a moderating factor. To the best of our knowledge, no study has investigated these relationships within a single comprehensive model. Existing research has examined these factors separately or through different methodological approaches, such as qualitative or case-based analyses. In this context, the study seeks to address the following research questions (RQs):

RQ1: To what extent do the levels of employee knowledge and awareness, perceived risks and benefits, and self-confidence directly impact their intention to use AI in the Indonesian financial services industry?
RQ2: To what extent does managerial support moderate the relationship between knowledge and awareness, perceived risks and benefits, self-confidence, and the intention to use AI in the Indonesian financial services industry?

This study makes three significant contributions to knowledge. First, it enhances the understanding of AI adoption dynamics in Indonesia's financial services industry by examining how levels of knowledge and awareness influence the intention to use AI, moderated by managerial support. It highlights that individuals with higher knowledge and awareness about AI are better equipped to recognize and appreciate its benefits, such as improved efficiency and customer service, and to reduce concerns about potential drawbacks like job displacement and data privacy issues (Chiu et al., 2021; Li et al., 2019). Second, it investigates how the perceived risks and benefits impacts intention to use AI, with managerial support as a moderating factor. By identifying specific concerns such as data security and technological expertise gaps, this study sheds light on barriers to AI adoption (Rana et al., 2022). Third, it examines the critical role of self-confidence in using AI and its effect on adoption intentions. Self-confidence, stemming from both individual employee competencies and organizational readiness, is essential for overcoming barriers to AI adoption (Al-Sharafi et al., 2023; Iyer & Bright, 2024). This study highlights that higher levels of self-confidence empower individuals to navigate and effectively utilize AI technologies, and suggests that training programs and managerial support are pivotal in building this self-confidence. By providing comprehensive training and fostering an environment that supports innovation, organizations can enhance their employees' confidence in using AI, thereby promoting higher adoption rates in the financial services industry.

The rest of this article is structured as follows. We begin with the theoretical background, proposed hypotheses and research methods used. This section is followed by our empirical findings and a final section which discusses implications for theory and practice.

2. Theoretical Background and Hypotheses

2.1. Previous research on AI adoption in the financial services industry

Previous research on AI adoption in the financial services sector provides valuable insights but demonstrates a notable over-reliance on qualitative methods, often neglecting the integration of diverse factors shaping adoption outcomes. For instance, Barile et al., 2024 employ case studies to propose strategic models for businesses using fully automated or hybrid robo-advisors, emphasizing the necessity of human interaction to meet customer needs. Aysan et al. (2024) provide a balanced scorecard analysis emphasizing workforce skills, ethical AI practices, and technological assimilation but do not examine psychological drivers such as perceived risks or self-confidence. Similarly, Sheth et al. (2022) adopt a qualitative thematic approach to highlight key areas such as operational skills, user awareness, managerial roles, and the importance of personalized services. While these studies offer meaningful perspectives, their qualitative nature limits generalizability and leaves a gap in understanding the comprehensive interplay of multiple psychological and managerial factors in AI adoption.

Although some studies adopt quantitative methodologies, they often focus on narrow aspects of AI adoption rather than integrating a broader spectrum of influencing factors. Nourallah (2023) provide a quantitative analysis emphasizing the role of trust propensity, performance expectancy, and hedonic motivation in fostering initial trust in financial robo-advisors but does not consider managerial support or awareness levels as potential contributors. Similarly, Salem and Rassouli (2025) highlight the influence of performance expectancy, social factors, and trust in shaping consumer attitudes toward AI-powered banking. However, these studies do not holistically account for how knowledge, perceived risks and benefits, and managerial interventions collectively drive adoption intentions.

The absence of integrative models that combine psychological and managerial factors leaves a significant gap in the literature on AI adoption in financial services. For example, while Chaouali et al. (2024) examine resistance to chatbots through combinations of barriers such as usage, risk, and tradition, these findings are limited to resistance rather than motivators of adoption. Similarly, Northey et al. (2022) focus on specific contexts, such as consumer trust in human versus robo-advisors, without addressing broader organizational or individual influences. To advance the field, our study offers a comprehensive model that incorporates levels of knowledge and awareness, perceived risks and benefits, self-confidence, and managerial support (Al-Sharafi et al., 2023; Chiu et al., 2021; Rana et al., 2022). This approach offers a more nuanced understanding of AI adoption, facilitating the development of effective strategies to improve acceptance and implementation within financial services contexts. Table 1 summarizes these studies.

2.2. The effect of knowledge and awareness levels on AI usage intention with managerial support as a moderator

According to innovation diffusion theory (IDT), the process of adopting an innovation like AI begins with gaining knowledge and awareness of it (Rogers, 2004). Knowledge involves an individual's

Table 1
Summary of empirical research and related studies on artificial intelligence (AI) adoption in the financial services industry.

No.	Authors	Methods	Gaps	Findings
1.	Aysan et al. (2024)	Balanced Scorecard (BSC)	Balanced Scorecard (BSC) applied to decision-making in AI implementation within the financial sector.	The results highlight how technological advancements significantly affect financial institutions' choices regarding AI adoption. By employing a unique quantitative approach, the research sheds light on critical aspects such as workforce skills, technology assimilation, and the promotion of ethical AI practices.
2.	Barile et al., 2024	Case Studies	Robo-Advisors platform models.	The findings present two distinct strategies for managing a business, each suited to either fully automated or hybrid robo-advisors (RAs), as demonstrated by the development of two platform model frameworks. The study highlights that solely depending on algorithms, without incorporating any human interaction in the service model, is insufficient to fulfill customer needs in the decision-making process.
3.	Chaouali et al. (2024)	fsQCA	Barriers to AI adoption in the banking sector.	The study's findings reveal four distinct sets of factors that may contribute to resistance to chatbots. These include: (i) a mix of usage, value, risk, and tradition-related barriers, (ii) a blend of value, risk, tradition, and image-related barriers, (iii) a combination of usage, value, risk, and image barriers, particularly among male participants, and (iv) a mix of usage, value, tradition, and image barriers, predominantly among female participants.
4.	Doumpos et al. (2023)	Agent-based model (ABM)	Provides a comprehensive review of AI-based research focused on the banking industry.	AI can influence banking efficiency, risk management, bank performance, banking regulation, and customer experiences.
5.	Nourallah (2023)	semPLS Package in R	Limited research has explored the ways in which young retail investors (YRIs) develop trust in financial robo-advisors (FRAs).	The results highlight that trust propensity, performance expectancy, and hedonic motivation play pivotal roles in fostering initial trust in financial robo-advisors (FRAs), which in turn drives the intention to use this technology. Although similarities are evident between Malaysia and Sweden, cultural variations influence the factors that shape young retail investors' (YRIs) trust in FRAs.
6.	Northey et al. (2022)	Experiments	To examine how financial advice from a human advisor (versus a robo-advisor) influences investment intentions in a retail banking context.	The findings from two experiments reveal that consumers exhibit greater trust in financial advice offered by human advisors compared to robo-advisors, particularly in scenarios requiring high involvement. The study further uncovers that trust in the advice provided and the perception of the bank's commitment to customer-centric practices serve as key drivers influencing subsequent investment intentions.
7.	Sheth et al. (2022)	Thematic analysis	Emphasizing human involvement and personalized service to enhance customer experience in AI-driven banking within emerging markets.	The findings outlined five core themes. The first theme highlights the significance of AI-driven banking and the essential skills required for operational efficiency. The second addresses the need for heightened user awareness regarding AI-powered banking systems. The third explores the role of managers and employees in promoting the value of AI-based interfaces. The fourth underscores the necessity of human involvement, influenced by users' demographic characteristics. Lastly, the fifth theme delves into the provision of personalized services within AI-mediated banking.
8.	Salem & Rassouli, 2025	PLS-SEM	Palestinian consumer attitudes toward AI-powered online banking with a focus on institutional trust	The study's results reveal that performance expectancy, effort expectancy, social influence, and facilitating conditions play pivotal roles in shaping consumer attitudes toward AI-driven online banking services. Additionally, trust in financial institutions acts as a moderating factor, amplifying the influence of these key variables on consumer perceptions. These insights highlight the importance of fostering trust alongside optimizing technological and social aspects to enhance consumer acceptance.

understanding of AI's functionalities, benefits, and applications, while awareness refers to recognizing AI's presence and its potential value. These foundational elements set the stage for forming positive perceptions toward AI adoption. Recent empirical research supports this view, highlighting the importance of knowledge and awareness in shaping intentions to use AI. For instance, Chiu et al. (2021) found that employees who possess a higher level of knowledge about AI are more inclined to adopt it, as they appreciate its potential to enhance efficiency and productivity. Similarly, Li et al. (2019) demonstrated that awareness of AI's capabilities and benefits significantly increases the likelihood of adoption by boosting employee perceptions of AI's utility and relevance. Together, these studies suggest that well-informed and aware employees are more likely to hold favorable attitudes toward AI, ultimately fostering a stronger inclination to integrate AI into their workflows.

Managerial support plays a critical moderating role in enhancing the relationship between knowledge, awareness, and employees' intentions to use AI. This support encompasses a range of managerial actions, such as allocating resources, cultivating a pro-innovation culture, and providing training opportunities. Recent research has highlighted the amplifying effect of managerial support on technology adoption. For example, Chen et al. (2021) revealed that when managers provide resources and encouragement, the positive impact of employee knowledge on AI adoption intentions is strengthened. Additionally, Li et al. (2019) demonstrated that managerial support mitigates perceived risks and uncertainties associated with new technologies, thereby enhancing the influence of awareness on employees' intention to use AI. These findings suggest that managerial support can effectively reinforce employees' confidence and enthusiasm for AI by mitigating uncertainties and solidifying the perceived benefits of AI, thus amplifying the positive effects of their knowledge and awareness on AI adoption.

Incorporating IDT, the diffusion of AI within an organization typically advances through several stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers et al., 2019). Managerial support is particularly crucial during the persuasion and implementation stages, where it directly influences employees' perceptions and adoption behaviors. During the persuasion stage, managers can actively advocate for AI, demonstrating its advantages and aligning it with organizational goals, thereby strengthening the favorable perceptions that employees form through knowledge and awareness. In the implementation stage, continuous managerial support ensures that employees are equipped with the necessary training and resources to utilize AI effectively, addressing potential challenges that arise (Norzelan et al., 2024; Pham et al., 2024). This sustained managerial support helps maintain momentum and facilitates a smoother transition to AI integration. This sustained support helps build momentum, facilitating a smoother and more successful integration of AI within the organization. Based on these theoretical arguments and empirical findings, our concurrent hypotheses are as follows:

Hypothesis 1a (H1a): *Higher levels of knowledge and awareness positively influence employees' intentions to use AI.*
Hypothesis 1b (H1b): *Managerial support moderates the relationship between knowledge and awareness and employee intention to use AI, such that the relationship is stronger when managerial support is high.*

2.3. The impact of perceived risks and benefits on AI usage intention with managerial support as a moderator

Perceived benefits refer to the positive outcomes employees expect from using AI, such as improved efficiency, enhanced decision-making, and increased productivity. On the other hand, perceived risks encompass concerns such as job displacement, data privacy issues, potential technological failures, and ethical dilemmas, all of which can deter AI adoption. Recent research supports these contrasting effects, with studies like Rana et al. (2022) and Schiavo et al. (2024) demonstrating that perceived benefits positively correlate with higher AI usage intentions, while perceived risks exert a negative influence on these intentions. Similarly, Chen et al. (2021) found that risks associated with AI create resistance among employees, reducing their willingness to engage with AI tools. Therefore, the interplay of perceived benefits and risks constitutes a critical determinant of employees' intentions to use AI.

Managerial support plays an essential moderating role in this relationship, influencing how perceived benefits and risks affect employees' intentions to adopt AI. By providing resources, training, and a clear vision for AI integration, managers can amplify perceived benefits while diminishing perceived risks. Li et al. (2019) suggest that managerial support fosters a supportive environment, instilling confidence in employees regarding AI adoption and reducing anxieties related to risks. This supportive environment enables employees to perceive AI more positively, which in turn increases their likelihood of using AI tools. In contrast, without managerial support, even high perceived benefits may not be sufficient to offset perceived risks, leading to lower adoption rates. Thus, managerial support can significantly boost the positive impact of perceived benefits and mitigate the negative effects of perceived risks on AI usage intention.

Protection motivation theory (PMT), developed by Rogers (1975), provides a useful framework for understanding these dynamics. PMT explains how individuals respond to threats and assess whether to take protective actions based on perceived risks and rewards. In the context of AI adoption, employees evaluate the perceived risks (such as job loss or technological failure) and benefits (such as increased productivity or efficiency) (Park et al., 2024). The theory posits that individuals will be more motivated to engage with a technology like AI if they perceive the benefits outweigh the risks, and if they believe they have the ability to cope with the potential challenges (self-efficacy) (Park et al., 2024). Managerial support can play a crucial role in enhancing self-efficacy and reducing perceived threats, thereby encouraging AI adoption. Through effective communication and support, managers can shape employees' perceptions of AI, making them feel more confident in their ability to use the technology and less concerned about the risks. Thus, PMT suggests that the combination of perceived risks, benefits, and the support provided by management will influence employees' intentions to adopt AI. Drawing on PMT and prior empirical research, we can develop the following hypotheses:

Hypothesis 2a (H2a): *Perceived risks and benefits negatively influence employees' intention to use AI.*
Hypothesis 2b (H2b): *Managerial support moderates the relationship between perceived risks and benefits and employees' intention to use AI, such that the relationship is stronger when managerial support is high.*

2.4. The influence of self-confidence on AI usage intention with managerial support as a moderating factor

Self-confidence reflects an individual's belief in their capacity to understand and effectively utilize AI, a factor that can significantly influence their willingness to engage with these technologies. Recent studies, such as those by Al-Sharafi et al. (2023) and Iyer and Bright (2024), indicate that individuals with higher self-confidence are more likely to adopt AI, as they perceive themselves as capable of navigating challenges and maximizing AI's potential benefits. Self-confident employees tend to approach AI with a problem-solving mindset, which strengthens their intention to use these tools in their work settings (Kim et al., 2024).

Managerial support serves as a critical moderator in the relationship between self-confidence and AI usage intention. Effective managerial support involves providing adequate training, resources, and a clear strategic vision for AI integration. According to Chen et al. (2021), managers who actively support AI initiatives contribute to building employees' confidence in their ability to adopt and utilize these technologies. This support might include hands-on training sessions, fostering a culture that encourages experimentation with AI, and offering ongoing feedback and encouragement. In environments with high managerial support, even employees with moderate self-confidence may develop a stronger intention to adopt AI, as the supportive setting alleviates concerns about potential failures. Conversely, without managerial support, even highly self-confident employees may encounter obstacles that hinder their willingness to engage with AI.

Self-determination theory (SDT), developed by Ryan and Deci (2000), emphasizes the importance of intrinsic motivation and the fulfillment of three basic psychological needs: autonomy, competence, and relatedness. In the context of AI adoption, SDT offers a useful framework for understanding how self-confidence and managerial support can influence an individual's intention to adopt AI (Kim et al., 2024). According to SDT, self-confidence is closely related to the need for competence, as individuals with higher self-confidence believe they are capable of mastering the skills required to use AI effectively (Ryan & Deci, 2000). Managerial support can fulfill both the autonomy and competence needs. When managers provide training and resources, they enhance employees' sense of competence, making them feel more capable of using AI. Additionally, by fostering an environment that encourages experimentation and self-directed learning, managerial support can satisfy employees' need for autonomy. When these needs are met, employees are more likely to be intrinsically motivated to adopt AI technologies, as they feel both capable and supported in their efforts. Therefore, SDT suggests that both self-confidence and managerial support are crucial drivers of AI adoption, with the interaction between these factors fostering a more motivated and capable workforce. Based on these insights and previous research, we formulate the following hypotheses:

Hypothesis 3a (H3a): *Higher levels of self-confidence among employees will positively influence their intention to use AI technologies.*
Hypothesis 3b (H3b): *Managerial support moderates the relationship between self-confidence and employees' intention to use AI, such that the relationship is stronger when managerial support is high.*

Fig. 1 illustrates the theoretical framework employed in this study.

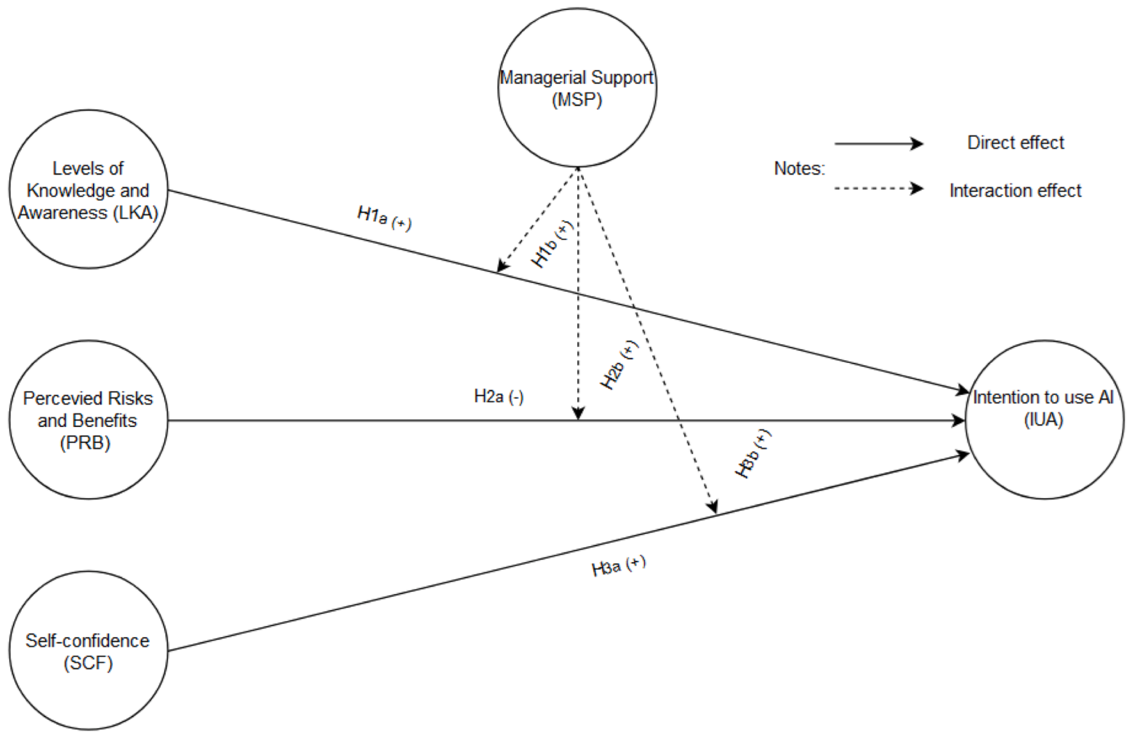

Fig. 1. Theoretical framework and pathways among latent variables.

3. Research methods

3.1. Participants and procedures

This study targeted employees in Indonesia's financial services industry, specifically those planning to integrate AI into their business processes. Data collection was conducted using Qualtrics (https://www.qualtrics.com/), a well-regarded platform for employee and customer surveys. Purposive sampling methods were employed to select participants based on two criteria. First, participants were lower-level employees with a minimum of three years of experience in the Indonesian financial services industry. Second, they were actively involved in AI-related pilot projects within their organizations. The final sample included 1,405 employees. To ensure representativeness, financial services institutions from each province were invited to participate in the survey.

The survey took place from April to May 2024. Employees in the financial industry who have adopted AI were invited to participate through personalized email invitations, each containing a unique survey link and detailed instructions. Participants were given one month to complete the survey, with extensions available if necessary. To improve response rates, weekly reminder emails were sent to non-respondents, with a final reminder issued the day before the survey closed, notifying participants that the data collection period would conclude the next day. Ethical approval was obtained, and informed consent was secured from all participants.

At the end of the research period and after survey completion, we obtained 492 fully completed questionnaires. We conducted quality checks on the survey data following Blasius and Thiessen's (2012) guidelines. First, the average response time was 15 min, aligning with established norms (Blasius & Thiessen, 2012). Second, we verified that no respondents completed the survey unusually quickly (e.g., within 1–3 days). Third, we included an attention-check question (Taplin, 2024): "We care about the data quality of our survey. Do you commit to providing thoughtful answers to the questions in the survey?" All respondents answered "yes." Fourth, we screened the data for missing values, straight-line responses, and outliers, excluding three questionnaires from the dataset (Newbold et al., 2023).

The final response rate was 34.59 %. Prior research, such as Holtom et al. (2022), has indicated that this response rate is relatively high and aligns with typical response rates observed in organizational research. Consequently, this response rate meets the minimum threshold for survey-based research, as proposed by Dillman et al. (2014). To verify that our sample size meets the minimum requirements for model estimation, we used G*Power 3 software (Faul et al., 2009). Based on our calculation with a power level of 0.99, an effect size of 0.15, and four predictors, we determined that a minimum sample size of 219 cases was required. Thus, our sample size not only meets but exceeds this minimum requirement, enhancing the power of our analysis.

The demographic characteristics of the participants (Cox & Holcomb, 2022), are as follows. The gender distribution showed that the majority of respondents were male, accounting for 59.05 % of the sample, while females made up 40.95 %. In terms of professional tenure, the largest group (37.86 %) had 10 to 15 years of work experience, followed by those with 5 to 10 years (29.22 %), and those with less than 5 years (19.14 %). Participants with more than 15 years of experience comprised 13.79 % of the sample. Additionally, 52.26 % of respondents were from the public sector of the financial services industry, while the remaining 47.74 % were from the private sector. Regarding age, the predominant age group was 35 to 45 years, representing 46.50 % of the participants.

3.2. Measures

The measurement items employed in this study were drawn from previous research studies, including those by Al-Sharafi et al. (2023), Chiu et al. (2021), Chen et al. (2021), and Rana et al. (2022). Approximately 21 relevant questions were identified as suitable for measuring the latent variables in our proposed model. To ensure the adequacy of these items in representing each construct, principal component analysis (PCA) via factor analysis was conducted. Validity and reliability of each variable were assessed to confirm the formation of a single factor.

Table 2
Results of validity and reliability assessment.

Measurement questions	Item	FA	SFL	AVE	MSV	ASV	RRC	ρ_c
Levels of Knowledge and Awareness (LKA) (*Source: Adapted from* Chiu et al., 2021)				0.636	0.223	0.134	0.899	0.901
I possess a significant level of knowledge and awareness regarding AI.	LKA1	0.845	0.811					
I lack considerable knowledge and awareness about AI (Reverse coded).	LKA2	0.882	0.853					
Within my circle of friends in the financial services industry, I am considered one of the “experts” on AI.	LKA3	0.825	0.760					
Compared to the majority of individuals in the financial services industry, my knowledge and awareness of AI are relatively low (Reverse coded).	LKA4	0.865	0.846					
Regarding AI, I genuinely lack substantial knowledge and awareness (Reverse coded).	LKA5	0.785	0.708					
Perceived Risks and Benefits (PRB) (*Source: Adapted from* Rana et al., 2022)				0.749	0.074	0.033	0.934	0.937
Given the risks and benefits, our financial services industry lacks the technological expertise necessary for full AI adoption.	PRB1	0.880	0.842					
Considering the risks and benefits, AI technology should not be employed for critical decision-making purposes in the financial services industry.	PRB2	0.907	0.883					
The integration of AI into business analytics solutions may present a greater technological risk than its benefits for our financial services industry.	PRB3	0.870	0.829					
AI integrated business analytics solutions may pose more security challenges than benefits to our financial services industry.	PRB4	0.921	0.910					
Our financial services industry lacks adequate security mechanisms for the complete adoption of AI.	PRB5	0.890	0.862					
Self-confidence (SCF) *(Source: Adapted from* Al-Sharafi et al., 2023)				0.718	0.241	0.132	0.865	0.867
I am confident in using AI products independently.	SCF1	0.805	0.644					
I have confidence in using AI products even without guidance.	SCF2	0.932	0.930					
I feel confident using AI products due to their clarity and ease of understanding.	SCF3	0.933	0.935					
Managerial Support (MSP) *(Source: Adapted from* Chen et al., 2021)				0.669	0.224	0.131	0.916	0.918
The managers explicitly show their support for adopting AI in our financial services industry.	MSP1	0.898	0.914					
Managers are open to taking risks associated with AI adoption in the financial services industry.	MSP2	0.901	0.910					
Our managers possess the capability to embrace new technologies ahead of our competitors.	MSP3	0.891	0.856					
Our managers can harness IT new technologies as a strategic core competency in our financial services industry.	MSP4	0.852	0.760					
Our managers have a solid grasp of how AI technology can enhance the business performance of our financial services industry.	MSP5	0.732	0.609					
Intention to use AI (IUA) (*Source: Adapted from* Chiu et al., 2021)				0.656	0.240	0.153	0.844	0.847
I plan to utilize the AI system in the future within our financial services industry.	IUA1	0.922	0.863					
I anticipate using the AI system in the future within our financial services industry.	IUA2	0.881	0.701					
I intend to use the AI system in the future within our financial services industry.	IUA3	0.933	0.855					

Note(s): FA = factor analysis; SFL = standardized factor loading; AVE = Average variance extracted; MSV = Maximum shared variance; ASV = Average shared variance; RRC = Raykov’s reliability coefficient; ρ_c = Composite reliability.

Using IBM SPSS 29.0 software, we obtained a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO-MSA) exceeding 0.50 for each latent variable, with a single component extracted. Additionally, factor loading values for each item surpassed 0.732, and Cronbach's alpha for each construct exceeded 0.869, confirming the presence of a single factor (Hair et al., 2019; Newbold et al., 2023). The complete list of the 21 selected items for this study is detailed in Table 2.

For the assessment of level of knowledge and awareness (LKA), perceived risks and benefits (PRB), self-confidence (SCF), managerial support (MSP), and intention to use AI (IUA), a variety of items were employed. Participants rated these items using a 5-point Likert scale, with 1 indicating "strongly disagree" and 5 representing "strongly agree".

3.3. Data analysis

For the data analysis in this study, we adopted covariance-based structural equation modeling (CB-SEM), a widely recognized statistical approach for exploring complex relationships among latent variables. CB-SEM is particularly well-suited for theory-driven research as it integrates confirmatory factor analysis (CFA) to validate measurement models while simultaneously evaluating structural models to test hypotheses. This dual functionality enables researchers to assess both the reliability and validity of constructs and the causal relationships posited in their theoretical frameworks. The method's capacity to provide robust parameter estimates while addressing measurement error makes it a preferred choice in empirical studies (Jöreskog et al., 2016). Furthermore, scholars such as Kline (2023) and Whittaker and Schumacker (2022) underscore its strengths in delivering unbiased results and managing complex model specifications effectively, ensuring rigor and precision in statistical analysis.

4. Results

In this study, we used SmartPLS 4 software for the CB-SEM estimation (Venturini et al., 2023). The CB-SEM algorithm in SmartPLS is particularly suited for handling non-normal data conditions, utilizing bootstrapping rather than the maximum likelihood (ML) estimator for calculating standard deviations (STDEV) in model estimation. Consequently, we conducted several preliminary tests, detailed in Appendix A, to ensure the appropriateness of our method. The outcomes of these preliminary tests validated our chosen approach.

We present the descriptive statistics for each variable in Table 3. From these results, we observe that the mean values for all latent variables are under 5, and the standard deviation (STDEV) values are all below 2. According to Cox and Holcomb (2022), these values are within acceptable ranges. Moreover, we calculated the variance inflation factor (VIF) for each predictor, finding that all VIF values were below 3.3 (refer to Table 3). Consequently, we conclude that our model does not suffer from multicollinearity issues (Kalnins & Praitis Hill, 2025).

4.1. Assessment of method biases

We rigorously examine two potential methodological biases in online surveys that might affect our results: non-response bias (Scheaf et al., 2023) and common method variance (Podsakoff et al., 2024). Our analysis, detailed in Appendix A, indicates that these methodological biases do not compromise the validity of our findings.

4.2. Assessment of validity and reliability

We evaluated the validity and reliability of the measurement items through confirmatory factor analysis (CFA) and assessed the model fit. As shown in Table 2, all items exhibited standardized factor loading (SFL) values above 0.701, and average variance extracted (AVE) values exceeded 0.636 for all constructs, with the exception of SCF1 and MSP5, which, while slightly lower at 0.609, are still considered acceptable. Thus, convergent validity is satisfied (Bandalos & Finney, 2019; Garson, 2023; Hoyle, 2023). Additionally, both the heterotrait-monotrait ratio (HTMT and HTMT2) ratios remained below 0.85, and both maximum shared variance (MSV) and average shared variance (ASV) values were smaller than the AVE values, as shown in Tables 2 and 3. Based on these results, our measurement items satisfy the criteria for divergent validity (Henseler, 2021).

Table 3
Divergent validity results, descriptive statistics and correlations among latent variables.

Latent variable	1	2	3	4	5
Intention to use AI (IUA)	*(0.85)*	0.428**	0.335**	-0.268**	0.490**
Levels of Knowledge and Awareness (LKA)	0.606	*(0.85)*	0.471**	-0.134**	0.329**
Managerial Support (MSP)	0.505	0.649	*(0.85)*	-0.133**	0.412**
Perceived Risks and Benefits (PRB)	0.293	0.150	0.142	*(0.85)*	-0.112**
Self-confidence (SCF)	0.467	0.406	0.386	0.026	*(0.85)*
Mean	3.783	4.080	3.783	3.632	3.836
Standard Deviation (STDEV)	1.048	0.930	1.048	1.168	0.973
Variance Inflation Factor (VIF)	–	2.752	2.655	1.036	1.799

Note(s): Below the diagonal are the HTMT values. Above the diagonal are the correlation values. Diagonal and bold elements are cut-off values for HTMT. ** The correlation of constructs is significant at the 0.01 level (2-tailed).

In the next phase, we assessed the reliability of constructs using Raykov's reliability coefficient (RRC) and composite reliability (ρ_c), which are deemed suitable for CFA. According to Raykov and Marcoulides (2011), values above 0.70 are recommended for both measures. Our analysis, detailed in Table 2, shows that values exceed 0.844 for both measures, aligning with the specified criteria. We then computed goodness-of-fit indices (GOFI) for our CFA model, yielding the following results: Comparative Fit Index (CFI) = 0.965 > 0.90; Normed Fit Index (NFI) = 0.947 > 0.90; Tucker-Lewis Index (TLI) = 0.931 > 0.90; Goodness of Fit Index (GFI) = 0.905 > 0.85; Adjusted Goodness of Fit Index (AGFI) = 0.897 > 0.85; Parsimony GFI (PGFI) = 0.645 > 0.60; and Root Mean Square Error of Approximation (RMSEA) = 0.014 < 0.08 (Jöreskog et al., 2016; Kline, 2023; Whittaker & Schumacker, 2022). Based on these GOFI results, indices meet the specified standards and indicate a good fit.

4.3. Assessment of the full model

We assessed the entire model using a bootstrapping procedure, particularly appropriate for handling non-normal data conditions. Employing 10,000 resamples to ensure robust estimates (Kline, 2023), we evaluated key metrics including *R*-square (R^2) and effect size (f^2). Regarding model performance, our proposed model produced an R^2 value of 0.586 for intention to use AI (IUA). According to Cohen et al. (2003), this R^2 value fall within the acceptable range for social science research. Additionally, to supplement the findings from hypothesis significance tests, we calculated f^2 values, which ranged from 0.059 to 0.149, all exceeding 0.02. These values confirm the extent to which the null hypothesis is false, thereby supporting the testing of the alternative hypothesis (Iacobucci et al., 2023).

4.4. Testing of hypotheses

We adhered to the methodology recommended by SEM experts for hypothesis testing, examining key parameters such as the beta coefficient (β), standard deviation (STDEV), p-value and t-statistic at a 5 % significance level (one-tailed test). Our approach was guided by the recommendations of Hoyle (2023) and Kline (2023). In this study, we utilized standardized estimates to simultaneously evaluate the hypotheses within the full model. The results of our model estimation, as shown in Table 4 and Fig. 2, consistently supported our proposed hypotheses. Notably, our research provides empirical evidence for the direct relationships between the level of knowledge and awareness (LKA), perceived risks and benefits (PRB), and self-confidence (SCF) in relation to the intention to use AI (IUA) among employees in the financial services industry. The beta (β) coefficients were 0.448 (STDEV = 0.069) for level of knowledge and awareness (LKA), -0.157 (STDEV = 0.029) for perceived risks and benefits (PRB), and 0.212 (STDEV = 0.064) for self-confidence (SCF), all with p-values < 0.05. Based on these findings, we confirm the validity of hypothesis 1a (H1a), hypothesis 2a (H2a), and hypothesis 3a (H3a).

In the final phase of our hypothesis testing, we examined the effects of the interactions between level of knowledge and awareness (LKA) × managerial support (MSP), perceived risks and benefits (PRB) × managerial support (MSP), and self-confidence (SCF) × managerial support (MSP) on the intention to use AI (IUA) among employees in the financial services industry. Our analysis revealed beta (β) values of 0.108 (STDEV = 0.031) for the interaction between LKA and MSP, 0.176 (STDEV = 0.034) for the interaction between PRB and MSP and 0.088 (STDEV = 0.031) for the interaction between SCP and MSP. The significance levels for these relationships were indicated by $p < 0.01$. Consequently, we affirm that our results strongly support hypothesis 1b (H1b), hypothesis 2b (H2b), and hypothesis 3b (H3b).

4.5. Robustness checks

We addressed two critical methodological concerns—endogeneity bias and the potential for non-linear relationships between variables—to ensure the robustness of our findings. Endogeneity bias, which can distort causal interpretations, was mitigated using a series of regression models employing the Gaussian copulas approach, implemented with Stata software. This technique evaluates the independence of error terms and regressors, thereby ensuring robust estimations. Analyzing the p-values derived from the Gaussian copulas test, we found no statistically significant values at the 5 % significance level. These findings, consistent with the recommendations of Park and Gupta (2012), confirm that our results are not affected by endogeneity bias.

Furthermore, we examined the potential for non-linear relationships among variables using Ramsey's regression specification error test (RESET) (Wooldridge, 2020). Such non-linear relationships, if present, could violate the linearity assumption critical for covariance-based structural equation modeling (CB-SEM). Following Wooldridge's (2020) guidelines, we applied the RESET procedure and found no significant p-values at the 5 % level. This outcome confirms that our model adheres to the linearity assumption, a prerequisite for CB-SEM, as emphasized by Whittaker and Schumacker (2022).

5. Discussion

The results of our study shed light the complex dynamics among levels of knowledge and awareness, perceived risks and benefits, self-confidence, and managerial support in influencing individuals' inclination to utilize artificial intelligence (AI) in Indonesia's financial services industry. First, our findings demonstrate a significant positive relationship between levels of knowledge and awareness and the intention to use AI. This implies that individuals with a deeper understanding of AI and and greater awareness of its potential are more predisposed to embrace AI technologies (Chiu et al., 2021; Li et al., 2019). This underscores the importance of educational efforts and awareness-raising initiatives in fostering favorable attitudes toward AI adoption (Yang, Hussain, Ammar Zahid, & Maqsood, 2025), particularly within Indonesia's financial services sector. Our results extend the work of Chiu et al. (2021), showing that both knowledge and high awareness levels play essential roles in AI adoption.

Table 4
Results of hypothesis confirmation.

Connection between latent variables	Coef (β)	STDEV	p-value	t-statistic	Finding
Direct effect					
Levels of Knowledge and Awareness (LKA) → Intention to use AI (IUA)	0.448	0.069	0.000***	6.542***	H1a supported
Perceived Risks and Benefits (PRB) → Intention to use AI (IUA)	-0.157	0.029	0.000***	7.372***	H2a supported
Self-confidence (SCF) → Intention to use AI (IUA)	0.212	0.064	0.001***	3.290***	H3a supported
Interaction effect					
Levels of Knowledge and Awareness (LKA) × Managerial Support (MSP) → Intention to use AI (IUA)	0.108	0.031	0.000***	3.368***	H1b supported
Perceived Risks and Benefits (PRB) × Managerial Support (MSP) → Intention to use AI (IUA)	0.176	0.034	0.000***	5.159***	H2b supported
Self-confidence (SCF) × Managerial Support (MSP) → Intention to use AI (IUA)	0.088	0.031	0.006**	2.763**	H3b supported

Note(s): Coef (β) = standardized beta coefficient; STDEV = standard deviation; **$|t| \geq 2.33$ at $p < 0.01$ level; ***$|t| \geq 3.09$ at $p < 0.001$ level.

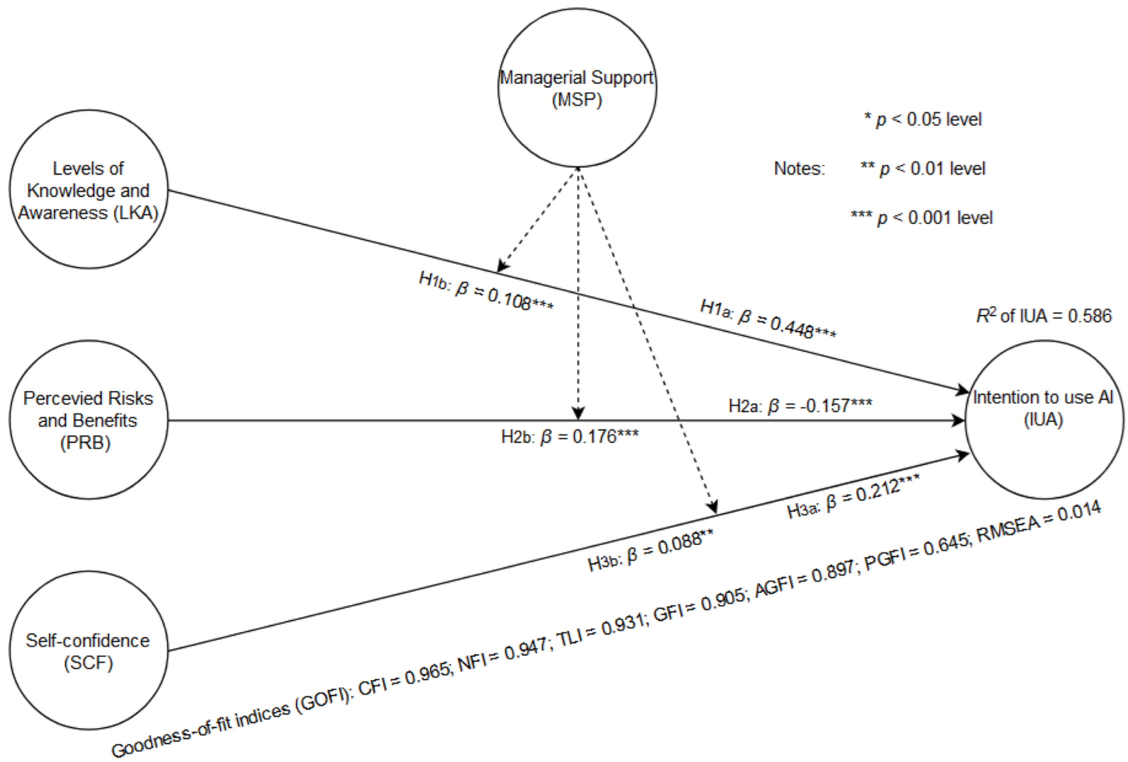

Fig. 2. Results obtained from structural equation modeling (SEM) analysis.

Second, our study highlights the influence of perceived risks and benefits on the intention to use AI. Consistent with our expectations, we found that perceived risks exert a stronger influence than perceived benefits, negatively impacting the intention to use AI (Rana et al., 2022; Schiavo et al., 2024). This nuanced finding suggests that individuals may be less incentivized by potential benefits and more deterred by perceived risks when considering AI adoption. Issues such as data privacy and ethical concerns in adopting AI in Indonesia's financial industry likely play a critical role, given the lack of comprehensive regulations governing these aspects. For instance, concerns about data breaches, unauthorized usage, and the potential misuse of sensitive financial information might intensify skepticism toward AI technologies. Furthermore, the absence of standardized frameworks for ethical AI implementation could exacerbate perceptions of risk among stakeholders. However, it is crucial to recognize that perceptions of risk may vary by context and AI application, warranting further investigation into how different types of perceived risks affect adoption intentions across various domains. Our findings extend Rana et al. (2022) by supporting their conclusion that employees perceive AI-related risks as outweighing the potential benefits in Indonesia's financial industry.

Third, our results indicate a significant positive relationship between self-confidence and intentions to use AI. Individuals who exhibit higher levels of self-confidence in their ability to use AI technologies are more likely to intend to use them (Al-Sharafi et al., 2023; Iyer & Bright, 2024). This finding underscores the role of self-efficacy beliefs in shaping technology adoption behaviors and highlights the need for initiatives aimed at boosting individuals' confidence in their AI-related skills (Kim et al., 2024). Our findings align with prior research by Al-Sharafi et al. (2023) and Kim et al. (2024), which showed that high self-efficacy in individuals can enhance their intention to use AI within Indonesia's financial sector.

Finally, our study reveals an interesting interaction effect between managerial support and the relationships among knowledge and awareness levels, perceived risks and benefits, self-confidence, and AI adoption intentions. Specifically, we found that managerial support moderates the impact of these factors on the intention to use AI. In organizations where managerial support for AI adoption is strong, the positive effects of knowledge and awareness levels, perceived risks and benefits, and self-confidence on AI adoption intentions are amplified. Conversely, in environments with limited managerial support, these factors have a weaker or negligible effect on AI adoption intentions (Chen et al., 2021; Li et al., 2019). his finding underscores the importance of organizational support and endorsement in facilitating AI adoption among employees, highlighting how leadership buy-in and supportive organizational cultures can drive successful AI initiatives. These findings build on prior research by Chiu et al. (2021), Rana et al. (2022), Al-Sharafi et al. (2023), and Kim et al. (2024), providing further evidence of the moderating role of managerial support in these relationships.

6. Conclusions

In conclusion, this study provides valuable insights into the complex factors influencing AI adoption in Indonesia's financial services sector. The findings highlight the critical roles of knowledge and awareness levels, self-confidence, and managerial support in shaping individuals' intentions to use AI. Specifically, higher levels of knowledge and awareness, along with increased self-confidence, were found to positively impact AI adoption intentions, while perceived risks were identified as significant barriers. Moreover, managerial support was shown to play a crucial moderating role, amplifying these factors and the intention to adopt AI. These findings underscore the need for targeted interventions, including training programs, leadership endorsement, and strategic initiatives, to foster a culture of innovation and trust in AI technologies. Ultimately, the study emphasizes that successful AI adoption in financial institutions requires a holistic approach that combines knowledge enhancement, confidence-building, and strong managerial support to overcome barriers and ensure long-term success in AI integration.

6.1. Theoretical implications

Our study provides important theoretical contributions to innovation diffusion theory (IDT), protection motivation theory (PMT), and self-determination theory (SDT) in the context of AI adoption. From an IDT perspective, our study extends the theory by incorporating variables such as levels of knowledge and awareness, which are critical to understanding the diffusion process of AI technologies. IDT traditionally focuses on the attributes of the innovation itself (e.g., relative advantage or compatibility) and the communication channels used to spread information about the innovation (Rogers, 2004). Our research enriches this model by emphasizing the psychological and cognitive factors that influence an individual's decision-making during the adoption process. Specifically, we highlight how knowledge and awareness play crucial roles in the early stages of the innovation-decision process (Rogers et al., 2019). By facilitating education programs and awareness campaigns, organizations can accelerate AI adoption by ensuring that potential adopters are well-informed about the technology's benefits and risks. This theoretical extension underscores the importance of user cognition and emotion in the diffusion process, providing a more comprehensive view of how new technologies are adopted.

Our integration of PMT also enhances the understanding of AI adoption. PMT focuses on how individuals assess threats and rewards, and subsequently decide to engage in protective behaviors in response (Rogers, 1975). In the case of AI, perceived risks, such as job displacement or ethical concerns, are crucial factors that influence whether individuals choose to adopt AI technologies. Our study suggests that successful adoption strategies must address these risks, while simultaneously highlighting the benefits of AI adoption (Park et al., 2024). We also show that managerial support can help mitigate perceived risks by fostering a sense of security and self-efficacy among employees. This approach aligns with PMT's emphasis on individuals' perceptions of their ability to overcome threats. Thus, our study not only extends the application of PMT to the AI adoption context but also emphasizes the need for a balanced approach that manages perceived risks while promoting the perceived rewards of AI.

Finally, our research contributes to SDT by highlighting the importance of intrinsic motivation in AI adoption. SDT posits that individuals are more likely to engage in behaviors that satisfy their psychological needs for competence, autonomy, and relatedness (Ryan & Deci, 2000). In the context of AI, self-confidence plays a key role in the adoption process. Employees who feel competent in using AI are more likely to adopt it, and this self-confidence can be fostered through managerial support, such as training and skill-building opportunities (Kim et al., 2024). Our findings suggest that managerial support systems are essential for building this competence and enhancing intrinsic motivation to engage with AI. By providing employees with the tools, resources, and encouragement they need to succeed, organizations can cultivate a positive environment that supports sustained AI usage. This extension of SDT within the AI adoption framework highlights the critical role of self-efficacy and motivation in influencing adoption outcomes.

6.2. Practical implications

In terms of practical implications, this study provides valuable insights for managers and policymakers in Indonesia's financial services industry. One of the key findings is that managers can leverage these insights to develop effective training programs aimed at enhancing employees' understanding of AI technologies. By focusing on increasing knowledge and awareness, managers can clarify AI's benefits and reduce resistance to its adoption, thereby fostering a culture of innovation. Addressing specific concerns with evidence-based responses can help build trust and confidence among employees, leading to higher adoption rates and improved organizational efficiency (Barile et al., 2024).

In addition to training programs, financial institutions can further enhance AI adoption by fostering a supportive organizational culture through strong managerial involvement. Managers play a crucial role in modeling AI adoption behaviors and setting clear expectations for their teams. By actively endorsing AI initiatives, communicating the potential of AI, and facilitating open discussions on its benefits and challenges, managers can create a positive environment for AI integration. Highlighting successful AI applications within the organization can help normalize AI adoption and showcase its practical value. Moreover, managers can act as change agents, providing continuous support and addressing concerns in a timely manner, thereby empowering employees and ensuring smoother transitions to AI technologies.

Second, beyond internal training and support, industry leaders can leverage these insights to drive strategic initiatives that align with broader business goals. Developing comprehensive AI strategies that emphasize the benefits of AI while addressing perceived risks can set industry standards for ethical AI implementation (Bankins & Formosa, 2023). For example, implementing robust data security measures and transparent policies, alongside ongoing employee training programs, can mitigate concerns about job displacement and foster AI acceptance among stakeholders. These efforts will not only enhance innovation but also improve operational efficiencies across the organization.

Finally, policymakers can play a pivotal role in creating regulatory frameworks that support the safe and effective deployment of AI within the financial sector (Zhang et al., 2023). By establishing clear guidelines for data protection, ethical AI usage, and employee rights, they can create an environment conducive to responsible AI adoption. Educational initiatives and public awareness campaigns are also vital in promoting AI benefits and dispelling misconceptions. By doing so, policymakers can help ensure that AI technologies enhance the resilience of the financial system while meeting the evolving needs of consumers.

6.3. Limitations and suggestions for future research

Our study has inherent limitations, and we propose several directions for future research. First, while we provide valuable insights, it is important to acknowledge that intentions do not always translate into actual behavior. Future studies could employ longitudinal or experimental designs to track AI technology adoption over time, offering a more nuanced understanding of the causal relationships among variables (Aguinis, 2024; Maier et al., 2023). Furthermore, our focus on the financial services industry limits the generalizability of our findings. Future research could replicate this study across diverse populations and countries to validate the robustness of these relationships in various contexts and demographics and enhance external validity (Aguinis, 2024).

Second, our study relies on self-reported data, which is inherently subjective and susceptible to biases. Future research could incorporate more objective measures, such as secondary data, to improve data reliability. Additionally, potential measurement errors may introduce uncertainty. Employing more robust methods, such as Rasch analysis (Engelhard & Wind, 2018), could help address these issues by providing superior error-handling capabilities.

Lastly, our study primarily focused on individual-level factors, overlooking the influence of organizational and contextual elements on AI adoption. Future research could investigate how organizational culture and managerial support impact individual intentions to use AI, providing a more holistic understanding of adoption dynamics. Exploring potential mediators, such as personality traits or social norms, could also reveal deeper mechanisms driving adoption behaviors.

CRediT authorship contribution statement

Ahyar Yuniawan: Writing – review & editing, Visualization, Software, Project administration, Investigation, Formal analysis, Conceptualization, Writing – original draft, Validation, Resources,

Methodology, Funding acquisition, Data curation. **Hersugondo Hersugondo:** Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition, Writing – original draft, Validation, Resources, Investigation, Conceptualization. **Fuad Mas'ud:** Writing – original draft, Validation, Resources, Methodology, Funding acquisition, Writing – review & editing, Visualization, Supervision, Project administration, Investigation, Conceptualization. **Hengky Latan:** Data curation, Investigation, Resources, Supervision, Visualization, Writing – review & editing, Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft. **Douglas W.S. Renwick:** Investigation, Supervision, Visualization, Writing – review & editing, Conceptualization, Methodology, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This research was funded by Diponegoro University through its World Class Research Program (B Category) for the fiscal year 2024. The authors gratefully acknowledge this financial support.

Appendix A

Preliminary tests

We carried out several preliminary tests during our analysis. Firstly, we used the Cramér–von Mises test and observed statistically significant skewness and kurtosis values at the 5 % significance level, indicating a non-normal data distribution (Byrne, 2016; Kline, 2023). Secondly, in our outlier analysis, we found that all cases had Z-scores below 2.58, which aligns with the established rule of thumb and indicates the absence of outliers (Newbold et al., 2023). Lastly, we assessed the heteroscedasticity of our data. Using the chi-square test, we detected no significant residual variance at the 5 % significance level, confirming that the assumption of homoscedasticity is satisfied.

Method bias tests

Initially, we focused on addressing potential non-response bias by conducting a multivariate analysis of variance (MANOVA) on various demographic variables, following Clottey and Benton (2020). Our analysis revealed no statistically significant differences in the main variable across different demographic categories, with a significance level set at 5 %. To further confirm these findings, we performed t-tests on early and late survey respondents, as suggested by Scheaf et al. (2023). Again, our analysis indicated no significant differences between the two groups. Based on these comprehensive analyses, we can confidently assert that our data collection process was not affected by non-response bias.

Next, we addressed potential common method variance (CMV) using the marker variable approach, a contemporary method endorsed by Podsakoff et al. (2024). We initially mitigated CMV through careful survey design, ensuring the separation of predictor and outcome variables. Following the systematic procedure outlined by Miller and Simmering (2023), we included a new variable in our questionnaire that was unrelated to the focal constructs. This variable was then evaluated using correlation coefficients and goodness of fit indices (GOFI). Upon analyzing the CFA marker, we found no significant correlations ($r < 0.083$ at $p > 0.05$) between the marker variable and our focal constructs. Additionally, the model incorporating the CFA marker yielded inferior GOFI compared to our main CFA model. Considering both sets of observations, we can confidently conclude that CMV did not influence our data collection process and does not threaten the validity of our findings.

References

Aguinis, H. (2024). *Research methodology: Best practices for rigorous, credible, and impactful research*. SAGE Publications.

Al-Sharafi, M. A., Al-Emran, M., Arpaci, I., Iahad, N. A., AlQudah, A. A., Iranmanesh, M., & Al-Qaysi, N. (2023). Generation Z use of artificial intelligence products and its impact on environmental sustainability: A cross-cultural comparison. *Computers in Human Behavior, 143*, Article 107708.

Armutcu, B., Tan, A., Ho, S. P. S., Chow, M. Y. C., & Gleason, K. C. (2024). The effect of bank artificial intelligence on consumer purchase intentions. *Kybernetes*. https://doi.org/10.1108/K-01-2024-0145

Aysan, A., Dincer, H., Unal, I. M., & Yüksel, S. (2024). AI development in financial markets: a balanced scorecard analysis of its impact on sustainable development goals. *Kybernetes*. https://doi.org/10.1108/K-05-2024-1181

Bandalos, D. L., & Finney, S. J. (2019). Factor analysis: Exploratory and confirmatory. In G. R. Hancock, L. M. Stapleton, & R. O. Mueller (Eds.), *The reviewer's guide to quantitative methods in the social sciences* (2nd ed., pp. 98–122). Routledge.

Bankins, S., & Formosa, P. (2023). The ethical implications of artificial intelligence (AI) for meaningful work. *Journal of Business Ethics, 185*(4), 725–740.

Barile, D., Secundo, G., & Bussoli, C. (2024). Exploring artificial intelligence robo-advisor in banking industry: A platform model. *Management Decision*. https://doi.org/10.1108/MD-08-2023-1324

Blasius, J., & Thiessen, V. (2012). *Assessing the Quality of Survey Data*. SAGE Publications.

Byrne, B. M. (2016). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (3rd ed.). Routledge.

Cao, L., Chen, C., Dong, X., Wang, M., & Qin, X. (2023). The dark side of AI identity: Investigating when and why AI identity entitles unethical behavior. *Computers in Human Behavior,, 143*, Article 107669.

Chaouali, W., Souiden, N., Aloui, N., Ben Dahmane Mouelhi, N., Woodside, A. G., & Ben Abdelaziz, F. (2024). Roles of barriers and gender in explaining consumers' chatbot resistance in banking: A fuzzy approach. *International Journal of Bank Marketing, 42*(7), 1867–1887.

Chen, H., Li, L., & Chen, Y. (2021). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics, 8*(1), 36–68.

Chiu, Y.-T., Zhu, Y.-Q., & Corbett, J. (2021). In the hearts and minds of employees: A model of pre-adoptive appraisal toward artificial intelligence in organizations. *International Journal of Information Management, 60*, Article 102379.

Clottey, T., & Benton, W. C. (2020). Technical note: Recommendations for assessing unit nonresponse bias in dyadic focused empirical supply chain management research. *Decision Sciences, 51*(2), 423–447.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Lawrence Erlbaum Associates.

Cox, K. S., & Holcomb, Z. C. (2022). *Interpreting basic statistics: A workbook based on excerpts from journal articles* (9th ed.). Routledge.

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and mixed mode surveys: The tailored design method* (4th ed.). Wiley.

Engelhard, G., & Wind, S. A. (2018). *Invariant measurement with raters and rating scales: Rasch models for rater-mediated assessments*. Routledge.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160.

Garson, G. D. (2023). *Factor analysis and dimension reduction*. R. Routledge.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Henseler, J. (2021). *Composite-based structural equation modeling: Analyzing latent and emergent variables*. Guildford Press.

Holtom, B., Baruch, Y., Aguinis, H., & Ballinger, G. A. (2022). Survey response rates: Trends and a validity assessment framework. *Human Relations,, 75*(8), 1560–1584.

Hoyle, R. H. (Ed.). (2023). *Handbook of structural equation modeling* (2nd ed.). Guilford Press.

Hussain, M., Yang, S., Maqsood, U. S., & Zahid, R. M. A. (2024). Tapping into the green potential: The power of artificial intelligence adoption in corporate green innovation drive. *Business Strategy and the Environment, 33*(5), 4375–4396.

Iacobucci, D., Popovich, D. L., Moon, S., & Román, S. (2023). How to calculate, use, and report variance explained effect size indices and not die trying. *Journal of Consumer Psychology, 33*(1), 45–61.

Iyer, P., & Bright, L. F. (2024). Navigating a paradigm shift: Technology and user acceptance of big data and artificial intelligence among advertising and marketing practitioners. *Journal of Business Research, 180*, Article 114699.

Jöreskog, K. G., Olsson, U. H., & Wallentin, F. Y. (2016). *Multivariate analysis with LISREL*. Springer.

Kalnins, A., & Praitis Hill, K. (2025). The VIF score. What is it good for? Absolutely nothing. *Organizational Research Methods, 28*(1), 58–75.

Kim, B.-J., Kim, M.-J., & Lee, J. (2024). The impact of an unstable job on mental health: the critical role of self-efficacy in artificial intelligence use. *Current Psychology, 43*(18), 16445–16462.

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (5th ed.). Gulford Press.

Li, J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management, 73*, 172–181.

Li, S., Younas, M. W., Maqsood, U. S., & Zahid, R. M. A. (2024). Tech for stronger financial market performance: The impact of AI on stock price crash risk in emerging market. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-10-2023-1717

Liu, P. C. Y., Wang, W., Wang, Z., & Yang, Y. (2024). Will artificial intelligence undermine the effects of guanxi on relationship performance? Evidence from China's banking industry. *Industrial Marketing Management, 116*, 12–25.

Maier, C., Thatcher, J. B., Grover, V., & Dwivedi, Y. K. (2023). Cross-sectional research: A critical perspective, use cases, and recommendations for IS research. *International Journal of Information Management, 70*, Article 102625.

Miller, B. K., & Simmering, M. J. (2023). Attitude toward the color blue: An ideal marker variable. *Organizational Research Methods, 36*(3), 409–440.

Newbold, P., Carlson, W. L., & Thorne, B. M. (2023). *Statistics for business and economics* (10th ed.). Pearson.

Northey, G., Hunter, V., Mulcahy, R., Choong, K., & Mehmet, M. (2022). Man vs machine: How artificial intelligence in banking influences consumer belief in financial advice. *International Journal of Bank Marketing, 40*(6), 1182–1199.

Norzelan, N. A., Mohamed, I. S., & Mohamad, M. (2024). Technology acceptance of artificial intelligence (AI) among heads of finance and accounting units in the shared service industry. *Technological Forecasting and Social Change, 198*, Article 123022.

Nourallah, M. (2023). One size does not fit all: Young retail investors' initial trust in financial robo-advisors. *Journal of Business Research, 156*, Article 113470.

Park, J., Yun, J., & Chang, W. (2024). Intention to adopt services by AI avatar: A protection motivation theory perspective. *Journal of Retailing and Consumer Services, 80*, Article 103929.

Park, S., & Gupta, S. (2012). Handling endogenous regressors by joint estimation using copulas. *Marketing Science, 31*(4), 567–586.

Pham, P., Zhang, H., Gao, W., & Zhu, X. (2024). Determinants and performance outcomes of artificial intelligence adoption: Evidence from U.S. Hospitals. *Journal of Business Research, 172*, Article 114402.

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology and Organizational Behavior, 11*, 17–61.

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2022). Understanding dark side of artificial intelligence (AI) integrated business analytics: Assessing firm's operational inefficiency and competitiveness. *European Journal of Information Systems, 31*(3), 364–387.

Raykov, T., & Marcoulides, G. A. (2011). *Introduction to psychometric theory*. Routledge.

Rogers, E. M. (2004). A prospective and retrospective look at the diffusion model. *Journal of Health Communication, 9*(sup1), 13–19.

Rogers, E. M., Singhal, A., & Quinlan, M. M. (2019). Diffusion of innovations. In D. W. Stacks, M. B. Salwen, & K. C. Eichhorn (Eds.), *An integrated approach to communication theory and research* (3rd ed., pp. 415–433). Routledge.

Rogers, R. W. (1975). A protection motivation theory of fear appeals and attitude change. *The Journal of Psychology, 91*(1), 93–114.

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55* (1), 68–78.

Salem, M. Z., & Rassouli, A. (2025). Analyzing the impact of trust in financial institutions on Palestinian consumer attitudes towards AI-powered online banking: understanding key influencing factors. *Competitiveness Review: An International Business Journal, 35(2), 391–408.*

Scheaf, D. J., Loignon, A. C., Webb, J. W., & Heggestad, E. D. (2023). Nonresponse bias in survey-based entrepreneurship research: A review, investigation, and recommendations. *Strategic Entrepreneurship Journal, 17*(2), 291–321.

Schiavo, G., Businaro, S., & Zancanaro, M. (2024). Comprehension, apprehension, and acceptance: Understanding the influence of literacy and anxiety on acceptance of artificial Intelligence. *Technology in Society, 77*, Article 102537.

Shamim, S., Yang, Y., Ul Zia, N., Khan, Z., & Shariq, S. M. (2023). Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy. *Journal of Business Research, 167*, Article 114168.

Sheth, J. N., Jain, V., Roy, G., & Chakraborty, A. (2022). AI-driven banking services: The next frontier for a personalised experience in the emerging market. *International Journal of Bank Marketing, 40*(6), 1248–1271.

Shuqair, S., Pinto, D. C., Lancelot Miltgen, C., & Viglia, G. (2024). When powerful artificial intelligence backfires. *International Journal of Hospitality Management, 120*, Article 103778.

Taplin, R. H. (2024). Quantifying data quality after removing respondents who fail data quality checks. *Current Issues in Tourism, 28*(16), 2570–2581.

Veglianti, E., Li, Y., Magnaghi, E., & De Marco, M. (2022). Understanding artificial intelligence: Insights on China. *Journal of Asia Business Studies, 16*(2), 324–339.

Venturini, S., Mehmetoglu, M., & Latan, H. (2023). Software packages for partial least squares structural equation modeling: An updated review. In H. Latan, J. F. Hair, Jr, & R. Noonan (Eds.), *Partial least squares path modeling: Basic concepts, methodological issues and applications* (2nd ed., pp. 113–152). Springer.

Whittaker, T. A., & Schumacker, R. E. (2022). *A beginner's guide to structural equation modeling* (5th ed.). Routledge.

Wooldridge, J. M. (2020). *Introductory econometrics: A modern approach* (7th ed.). Cengage Learning.

Yang, J., Blount, Y., & Amrollahi, A. (2024). Artificial intelligence adoption in a professional service industry: A multiple case study. *Technological Forecasting and Social Change, 201*, Article 123251.

Yang, S., Hussain, M., Ammar Zahid, R. M., & Maqsood, U. S. (2025). The role of artificial intelligence in corporate digital strategies: evidence from China. *Kybernetes, 54*(5), 3062–3082.

Zhang, J., Li, X., & Tong, T. (2023). A tale of two types of standard setting: Evidence from artificial intelligence in China. *Journal of Management, 50*(4), 1393–1423.