The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/2050-3806.htm

Aslib Journal of Information Management

Beyond the hype: understanding barriers to AI adoption through lens of protection motivation theory

Ahyar Yuniawan, Hersugondo Hersugondo and Fuad Mas'ud
Department of Management, Diponegoro University, Semarang, Indonesia
Hengky Latan
Department of Statistics, Economics and Management, HLC Consulting, Semarang, Indonesia
Murad Ali
Newcastle Business School, Northumbria University, Newcastle upon Tyne, UK, and
Moacir Godinho Filho
Metis Lab, EM Normandie Business School, Le Havre, France

Received 6 August 2024
Revised 16 September 2024
26 March 2025
Accepted 29 March 2025

Abstract

Purpose – This study explores how perceived self-threat, skepticism and distrust influence employees' intentions to adopt artificial intelligence (AI), both directly and indirectly, through anticipated adverse outcomes.

Design/methodology/approach – Using protection motivation theory (PMT) as a theoretical framework, data were gathered from 597 employees. This study employed covariance-based structural equation modeling (CB-SEM) to evaluate the proposed hypotheses.

Findings – The results indicate that perceived self-threat, skepticism and distrust significantly and negatively impact employees' intention to use AI. Specifically, elevated levels of these psychological factors heighten concerns about privacy and job security, which in turn diminish the likelihood of AI adoption.

Originality/value – This study provides new insights into how perceived self-threat, skepticism and distrust affect AI adoption intentions through anticipated adverse outcomes. It enriches the literature by highlighting the psychological barriers to AI adoption and underscores the need for targeted managerial strategies to address these challenges.

Keywords Artificial intelligence, Anticipated adverse outcomes, Perceived self-threat, Skepticism, Distrust, Protection motivation theory

Paper type Research paper

1. Introduction

The adoption of artificial intelligence (AI) in the banking sector has surged in recent years, fundamentally transforming operations, customer interactions, and risk management (Booyse and Scheepers, 2024; Cintamür, 2024; Omoge *et al.*, 2022). Recent projections indicate that the global AI market in banking is expected to reach USD 310 billion by 2033, with a robust compound annual growth rate (CAGR) of 31.8% from 2023 (Spherical Insights, 2024). Banks are increasingly leveraging AI for predictive analytics, fraud detection, chatbots, and personalized services, enhancing both operational efficiency and customer satisfaction (Chaouali *et al.*, 2024; Manser Payne *et al.*, 2021; Vasiliu and Yavetz, 2024). Furthermore, approximately 80% of banks are already either employing or planning to implement AI technologies to optimize services and maintain a competitive edge in the evolving financial

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: 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.

Aslib Journal of Information Management

e-ISSN: 2050-3814
p-ISSN: 2050-3806
DOI 10.1108/AJIM-08-2024-0619

landscape (Lin and Lee, 2024; Manser Payne *et al.*, 2018; Rahman *et al.*, 2023). This widespread adoption underscores the critical role AI plays in modernizing banking operations.

Despite the significant benefits offered by AI, such as increased efficiency and enhanced customer service, its integration also presents notable challenges and risks (Gamble, 2020; Gligor *et al.*, 2021; Labrecque *et al.*, 2024). Recent surveys indicate that nearly 60% of banks have encountered cybersecurity threats linked to AI integration, with data breaches and fraud incidents increasing by 35% over the past two years (Spherical Insights, 2024). Additionally, 45% of banking institutions report biases in AI algorithms, raising concerns about fairness and discrimination in decision-making processes (Spherical Insights, 2024). The rapid deployment of AI has also exacerbated regulatory compliance issues, with 40% of banks struggling to align AI-driven practices with the existing financial regulations (Booyse and Scheepers, 2024; Northey *et al.*, 2022; Rautiainen *et al.*, 2024).

To date, research on barriers to AI adoption in banking has predominantly focused on organizational challenges, often neglecting the crucial role of individual-level factors. For instance, Kumar *et al.* (2024) identified significant organizational obstacles such as insufficient regulations, limited awareness, high implementation costs, and a shortage of skilled professionals as major impediments to AI integration. Similarly, Chang and Hsiao (2024) examined how barriers related to value and risk contribute to resistance toward AI-powered chatbots, with additional factors, such as tradition and image, exacerbating negative emotions. Rana *et al.* (2022) further emphasized governance issues, low data quality, and inadequate training as key factors that create opacity in AI-driven business analytics, leading to operational inefficiencies. While these studies offer valuable insights into institutional barriers, they largely overlook individual-level factors such as perceived self-threat, skepticism, distrust, and anticipated adverse outcomes, which may significantly influence employees' willingness to adopt AI (Lins *et al.*, 2024).

This gap is particularly important because individual perceptions and attitudes are critical to the successful adoption and implementation of AI technologies within organizations, especially in highly regulated sectors, such as banking. Previous research, by focusing predominantly on organizational challenges, has largely ignored personal concerns, such as the fear of job displacement (perceived self-threat), doubts about AI's reliability and benefits (skepticism), distrust in AI implementation, and concerns about negative outcomes (Carpenter *et al.*, 2019; Lins *et al.*, 2024; Chiu *et al.*, 2021). These psychological and emotional barriers can substantially impact employees' resistance to and acceptance of AI. Addressing these individual concerns is crucial for developing effective strategies to foster AI adoption. Therefore, this study aims to bridge this gap by investigating how perceived self-threat, skepticism, and distrust shape employees' intentions to adopt AI in the banking sector, with anticipated adverse outcomes serving as a mediating factor. By shifting the focus from organizational constraints to individual-level barriers, this study contributes to a more holistic understanding of AI adoption in banking, and offers insights into strategies for mitigating employee resistance.

Protection motivation theory (PMT) offers a valuable lens through which to understand the individual-level factors influencing AI adoption in the banking sector. According to PMT, individuals evaluate the threat posed by a potential risk and their ability to cope with that threat, which then affects their intention to engage in protective behaviors (Au and Tsang, 2023; Soral *et al.*, 2022). In the context of AI adoption, this theory can be applied to explore how employees perceive the risks associated with AI technologies and their beliefs about their capacity to mitigate them (Khan and Pandey, 2022; Park *et al.*, 2024). For example, employees who perceive AI as a threat to job security (perceived self-threat) may experience heightened anxiety, leading to resistance to AI adoption. Similarly, skepticism about AI's reliability and effectiveness can undermine employees' confidence in the technology, whereas distrust in its implementation or concerns about potential negative outcomes can further influence their reluctance to adopt AI. By applying PMT, our research aimed to dissect how these perceptions and attitudes impact employees' intentions to adopt AI, offering insights into how to address these concerns effectively.

Given these issues, we address the following research questions (RQs).

RQ1. To what extent do perceived self-threat, skepticism, and distrust directly influence employees' intention to adopt AI in the banking sector?

RQ2. To what extent do perceived self-threat, skepticism, and distrust indirectly affect employees' intention to use AI in the banking sector through anticipated adverse outcomes?

This study makes three key contributions to the field. First, it addresses the call by Kumar *et al.* (2024) for empirical research on barriers to AI adoption, shifting the focus from the widely studied benefits of AI to the often-overlooked challenges that employees face. While much of the existing literature emphasizes AI's potential advantages of AI, its integration into the banking sector remains fraught with concerns related to perceived self-threat, skepticism, and distrust (Booyse and Scheepers, 2024; Cintamür, 2024). By examining these psychological barriers, this study presents a more nuanced understanding of AI adoption, moving beyond organizational factors to highlight the individual-level hesitations that shape employees' willingness to embrace AI technology.

Second, this study deepens the discussion initiated by Chaouali *et al.* (2024) and Chang and Hsiao (2024) by exploring the mediating role of anticipated adverse outcomes—such as fears of job displacement and privacy risks—in the relationship between these barriers and AI adoption intentions. Unlike prior studies that focus on resistance in broad terms, this study disentangles the ways in which perceived risks translate into concrete reluctance, offering empirical insights into the mechanisms that amplify AI skepticism and distrust (Gligor *et al.*, 2021; Labrecque *et al.*, 2024).

Finally, this study expands the application of protection motivation theory (PMT) beyond its conventional domains by demonstrating its relevance in the context of AI adoption (Khan and Pandey, 2022; Park *et al.*, 2024). By integrating psychological responses to AI threats within the PMT framework, this study underscores the theory's versatility in explaining how individuals assess and react to emerging technologies. This theoretical extension provides a stronger foundation for understanding the cognitive and emotional processes underlying AI resistance, paving the way for future research on interventions that could mitigate these concerns.

The remainder of this paper is organized as follows. We begin with a review of the theoretical background, followed by the proposed hypotheses and research methods used. This is followed by a presentation of our empirical findings, and the article concludes with a discussion of the implications for theory and practice.

2. Theoretical background and hypotheses

2.1 Protection motivation theory (PMT)

Protection motivation theory (PMT), developed by Ronald Rogers in the 1970s, was initially applied to health-related behaviors, such as quitting smoking, using seatbelts, and following medical advice. This theory suggests that individuals evaluate threats through two key components: threat appraisal and coping appraisal. Threat appraisal involves assessing the severity and likelihood of a threat, whereas coping appraisal focuses on the perceived effectiveness of strategies to address the threat (Au and Tsang, 2023; Park *et al.*, 2024). Together, these evaluations influence an individual's motivation to adopt protective behaviors.

In the context of AI adoption, PMT has been adapted to explore how employees perceive and respond to the risks associated with integrating AI technologies into their workplaces (Khan and Pandey, 2022; Park *et al.*, 2024). The adoption of AI brings several risks, including the fear of job displacement due to automation, privacy concerns regarding the handling of personal data, and ethical challenges related to AI-driven decision-making. PMT provides a framework to analyze these risks by examining employees' perceptions of the severity and likelihood of these consequences (Soral *et al.*, 2022). For example, employees in sectors such as banking, where AI has a significant impact, may feel more vulnerable to job loss if they lack the skills to keep pace with technological advancement.

Furthermore, PMT emphasizes coping strategies, which include organizational policies, government regulations, personal efforts (such as skill development), and technological safeguards aimed at mitigating AI-related risks (Park *et al.*, 2024; Au and Tsang, 2023). Individuals' beliefs about the effectiveness of these measures (response efficacy) and confidence in their ability to implement them (self-efficacy) play a crucial role in their decision to adopt or resist AI technologies. In this study, we applied PMT to investigate how perceived self-threat, skepticism and distrust influence employees' intention to adopt AI, with anticipated negative outcomes acting as a mediating factor.

2.2 Previous research on the barriers to AI adoption

The literature on AI adoption reveals a diverse set of barriers across organizational dimensions. Rana *et al.* (2022) emphasize the organizational challenges, highlighting how inadequate governance, poor data quality, and ineffective employee training contribute to opacity in AI-driven business analytics. This lack of transparency leads to suboptimal decision-making, operational inefficiencies, and ultimately, a competitive disadvantage for firms, as evidenced by declining sales and employee dissatisfaction. Similarly, Kamoonpuri and Sengar (2023) identified customer-related barriers, such as reluctance to use AI chatbots, as the most critical obstacle for retailers, followed by technical and financial barriers. Rahman *et al.* (2023) extend the discussion by examining the role of individual attitudes, trust, and perceived risk in the intention to adopt AI within the banking sector, finding that these factors significantly impact adoption decisions, while perceived ease of use and awareness play a less significant role.

Focusing on AI resistance, several studies have explored the emotional and psychological factors that influence adoption decisions. Chang and Hsiao (2024) demonstrate how barriers related to value, risk, and tradition generate negative emotions and intensify resistance to chatbots. Their findings also revealed that a variety of barriers, such as usage and image, directly influence the intention to resist AI. Similarly, Chaouali *et al.* (2024) identified four unique combinations of factors differentiated by gender that contribute to chatbot resistance, such as usage and tradition among females and usage and risk among males. Finally, Vasiliu and Yavetz (2024) examined how demographic variables shape AI adoption and found that age, income, and education level significantly correlate with individuals' fear of being replaced by AI and their willingness to adopt it. Table 1 summarizes these studies.

2.3 The effect of perceived self-threat on the intention to use AI through anticipated adverse outcomes

The adoption of artificial intelligence (AI) in the banking sector has raised concerns among employees regarding job security and professional relevance (Chaouali *et al.*, 2024; Presbitero and Teng-Calleja, 2023). Perceived self-threat, which refers to the fear that AI technologies could undermine one's role, reduce job opportunities, or lead to displacement, plays a crucial role in shaping employees' attitudes toward AI adoption (Carpenter *et al.*, 2019; Wong *et al.*, 2024). In the banking industry, where automation and AI technologies are increasingly integrated into various functions, such as fraud detection, customer service, and risk management, employees may view AI as a direct threat to their job stability (Chang and Hsiao, 2024). This perception of self-threat is likely to negatively influence their intention to adopt AI (Wong *et al.*, 2024). Employees may resist adopting AI if they believe that it could lead to job loss or diminish their value within the organization (Vasiliu and Yavetz, 2024).

Table 1. Summary of empirical research and related studies on barriers to artificial intelligence (AI) adoption

No.	Authors	Variables	Findings
1	Wong *et al.* (2024)	Perceived self-threat, Privacy empowerment, Propensity to trust, Responsible corporate privacy and Regulatory protection	This research demonstrates that perceived self-threat, trust propensity, and regulatory protection significantly influence users' trust in AI usage, while privacy empowerment and corporate privacy responsibility do not have a notable impact
2	Vasiliu and Yavetz (2024)	Age, Income, Education level, Fear of being replaced by AI technologies and Willingness to adopt new AI technologies	This study found that age was negatively correlated with both the fear of being replaced by AI technologies and the willingness to adopt them Income showed a negative correlation with the fear of being replaced by AI. Additionally, education level was negatively correlated with the fear of being replaced, while positively correlated with the willingness to adopt AI technologies
3	Kumar *et al.* (2024)	Barries: Lack of acceptance, Lack of awareness, Data privacy, Inadequate regulations, Fear, High adaptation cost, Lack of compatibility	The research highlights key barriers hindering the adoption of AI in the healthcare sector, including insufficient regulations, limited awareness, high implementation costs, and a shortage of skilled AI professionals
4	Cintamür (2024)	Technology anxiety, Risk aversion, Performance expectancy, Emotions and Willingness to adopt artificial intelligence devices	The study's findings reveal that technology anxiety and risk aversion negatively moderate the relationship between performance expectancy and emotions, as well as the relationship between emotions and the willingness to adopt artificial intelligence devices in the banking sector
5	Chaouali *et al.* (2024)	Gender, Usage barrier, Value barrier, Risk barrier, Tradition barrier, Image barrier and Resistance to chatbots	The study's results indicate that the sample presents four possible combinations of factors that may explain resistance to chatbots: (i) a combination of usage, value, risk, and tradition barriers, (ii) a combination of value, risk, tradition, and image barriers, (iii) a combination of usage, value, risk, and image barriers, specifically among males, and (iv) a combination of usage, value, tradition, and image barriers, specifically among females
6	Chang and Hsiao (2024)	Usage barrier, Value barrier, Risk barrier, Tradition barrier, Image barrier, Emotion and Intentions to resist use of online chatbot	The study's findings confirmed that various barriers contribute to negative emotions and intensify resistance to chatbots. In particular, value and risk barriers were found to directly influence the intention to resist using online chatbots. Additionally, usage, value, risk, tradition, and image barriers were shown to positively impact negative emotions

(*continued*)

Table 1. Continued

No.	Authors	Variables	Findings
7	Barari *et al.* (2024)	Privacy concerns, Perceived risks, Customer alienation, Uniqueness neglect, Perceived benefits, Trust, Attitude, Satisfaction, Purchase decisions, Loyalty and Well-being	This research highlights the adverse effects of AI, such as privacy concerns, perceived risks, customer alienation, and neglect of individuality, which significantly and negatively impact customers' cognitive responses (perceived benefits, trust), affective responses (attitude, satisfaction), and behavioral outcomes (purchase decisions, loyalty, well-being)
8	Rahman *et al.* (2023)	Perceived ease of use, Perceived usefulness, Awareness, Perceived risk, Trust, and Subjective norms, Attitude toward AI and Intention to adopt AI in banking services	The study's findings reveal that attitude toward AI, perceived usefulness, perceived risk, trust, and subjective norms significantly impact the intention to adopt AI in banking services, whereas perceived ease of use and awareness do not. Additionally, the results demonstrate that attitude toward AI plays a significant mediating role in the relationship between perceived usefulness and the intention to adopt AI in banking services
9	Kamoonpuri and Sengar (2023)	Customer-related barriers, Marketing barriers, Technical barriers, Socio-cultural barriers, Organizational barriers, Financial barriers and Operational barriers	The study's findings indicate that customer-related barriers are the most critical obstacles, followed by technical and financial barriers, which retailers encounter when implementing AI chatbots
10	Rana *et al.* (2022)	Lack of governance, Poor data quality, Inefficient training, Perceived risk, Suboptimal decision, Operational inefficiency, Negative sales growth, Employee dissatisfaction, Firm's competitive disadvantage	The research findings revealed that insufficient governance, inadequate data quality, and ineffective training of key employees contribute to opacity in AI-integrated business analytics. This opacity leads to suboptimal decision-making and heightened perceived risk, ultimately causing operational inefficiencies. These inefficiencies, in turn, significantly drive negative sales growth and employee dissatisfaction, leading to a competitive disadvantage for the firm

Source(s): Authors' own work

Anticipated adverse outcomes, such as job displacement, skill redundancy, or diminished professional roles, serve as mediators between perceived self-threat and the intention to use AI in banking. According to protection motivation theory (PMT), individuals assess threats based on the severity and likelihood of negative outcomes and their ability to cope with these risks (Au and Tsang, 2023). In this context, employees who perceive a high level of self-threat from AI are more likely to anticipate the adverse consequences of AI adoption, which, in turn, reduces their intention to use these technologies (Khan and Pandey, 2022; Park *et al.*, 2024). For example, a bank employee who fears losing their job due to AI-driven automation is more likely to anticipate negative outcomes and resist adopting AI regardless of the perceived efficiency gains (Ali *et al.*, 2023; Omoge *et al.*, 2022). Based on these insights, the following hypotheses were derived:

H1a. Perceived self-threat has a negative effect on the intention to use AI.

H1b. Anticipated adverse outcomes mediate the relationship between perceived self-threat and the intention to use AI.

2.4 The impact of skepticism on the intention to use AI through anticipated adverse outcomes

Skepticism refers to doubts regarding the reliability, effectiveness, and long-term benefits of AI technologies (Lins *et al.*, 2024). In the banking sector, employees often encounter skepticism due to concerns about the transparency and accuracy of AI-driven decision making, potential biases in algorithms, and fear that the technology may not function as intended, particularly in critical areas such as fraud detection, risk assessment, and customer service (Booyse and Scheepers, 2024; Lin and Lee, 2024; Manser Payne *et al.*, 2018). When employees experience skepticism about AI, they are more likely to anticipate adverse outcomes such as operational inefficiencies, ethical concerns, or technological failures, which can negatively impact their intention to adopt AI (Gligor *et al.*, 2021; Rana *et al.*, 2022).

According to protection motivation theory (PMT), individuals assess potential risks and benefits before deciding to engage with or avoid a particular technology (Khan and Pandey, 2022; Park *et al.*, 2024). Skeptical employees may perceive the risks associated with AI as being more severe or likely to materialize, leading them to anticipate negative consequences, such as reduced job control, increased errors in AI-based systems, or potential regulatory challenges (Lins *et al.*, 2024). These anticipated adverse outcomes serve as mediating factors that amplify the negative influence of skepticism on intention to use AI. Furthermore, skepticism often fosters distrust in the organization's capacity to effectively manage AI implementation, which can further intensify employees' fear of adverse outcomes (Chiu *et al.*, 2021; Vasiliu and Yavetz, 2024). For instance, if an employee doubts the effectiveness of an AI system in performing tasks, such as credit scoring or fraud detection, they are more likely to foresee negative consequences, such as erroneous decisions or increased security risks. This heightened perception of adverse outcomes can reduce employees' confidence in the technology, leading to a lower intention to engage with AI systems (Chang and Hsiao, 2024). Based on these insights, the following hypotheses can be derived:

H2a. Skepticism has a negative effect on the intention to use AI.

H2b. Anticipated adverse outcomes mediate the relationship between skepticism and the intention to use AI.

2.5 The influence of distrust on the intention to use AI through anticipated adverse outcomes

Distrust refers to a lack of confidence in the reliability, security, and efficacy of AI technologies and their implementations (Lins *et al.*, 2024). In the banking sector, distrust can stem from concerns about data privacy, algorithmic biases, and the overall transparency of AI systems used in critical functions, such as credit assessment, fraud detection, and customer service (Gkinko and Elbanna, 2023; Salem and Rassouli, 2024). When employees harbor distrust of AI, they are more likely to anticipate negative outcomes associated with their use.

According to protection motivation theory (PMT), individuals evaluate potential threats based on their perceptions of severity, likelihood, and ability to cope with these threats (Au and Tsang, 2023; Khan and Pandey, 2022). Distrust in AI systems can amplify concerns about possible adverse consequences such as data breaches, erroneous decision-making, and ethical issues (Lins *et al.*, 2024). Employees who lack trust in AI technologies are likely to foresee such negative outcomes, which can significantly influence their intentions to use AI. For example, an employee who doubts the security measures of an AI-driven fraud-detection system may anticipate a higher risk of data breaches or false positives. This anticipation of adverse outcomes, driven by distrust, can undermine their willingness to adopt or engage in AI technologies (Barari *et al.*, 2024; Papagiannidis *et al.*, 2023). Distrust can thus create a barrier to AI adoption by increasing perceived risks and diminishing perceived benefits, as individuals are more inclined to resist technologies they believe could lead to detrimental effects (Chiu *et al.*, 2021). Based on these insights, we can formulate the following hypotheses:

H3a. Distrust has a negative effect on the intention to use AI.

H3b. Anticipated adverse outcomes mediate the relationship between distrust and the intention to use AI.

Figure 1 depicts the relationships between the variables in the proposed model.

3. Research methods

3.1 Participants and procedures

The sample for this study comprised employees working in the Indonesian banking sector, who were selected using a purposive sampling method based on specific criteria. First, the selected employees worked in banks that were involved in pilot projects related to AI implementation. Second, they were employed in banks that had already integrated AI into their business. Finally, all sampled employees had at least one year of experience working with AI. These criteria ensured that respondents had sufficient exposure to AI in banking, making them suitable for the study.

To collect data, an online survey was conducted using the Qualtrics platform (https://www.qualtrics.com/), which is a widely recognized tool for employee and customer research. Unlike platforms such as Amazon Mechanical Turk (MTurk) and Prolific, which primarily recruit participants from specific countries such as the US and the UK (Litman and Robinson,

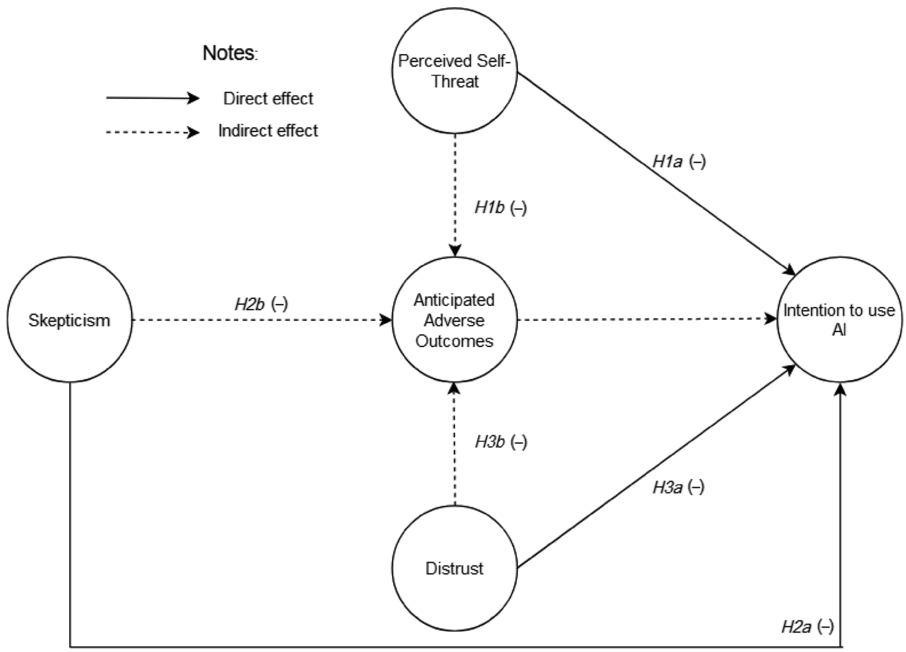

Figure 1. Theoretical model and hypotheses involving latent variables. **Source:** Authors' own work

2021), Qualtrics offers a global reach, making it more suitable for the Indonesian context. This study targeted employees within the country's banking industry, which consists of over two million workers across the government and private sectors. However, the Qualtrics panel available for this study comprised only 1,733 eligible employees, reflecting a subset of the broader population.

The data-collection process was designed to ensure efficiency and data quality. The survey was conducted from April to May 2024, with selected employees invited via personalized email invitations containing a unique survey link and detailed instructions. Participants had one month to complete the survey, with a possible extension of seven days if necessary. Informed consent and ethical approval were obtained before participation. To encourage participation and improve response rates, each respondent received a prepaid credit reward of IDR 25,000. Additionally, weekly reminder emails were sent to non-respondents, culminating in a final reminder three days before the survey was closed.

At the end of the data-collection period, 624 completed responses were obtained. Data screening was performed to exclude 27 respondents owing to incomplete information or missing data, resulting in a final response rate of 34.45%. According to Pielsticker and Hiebl (2020), who analyzed survey response trends over several decades, this rate is relatively high and aligns with the commonly observed response rates in survey-based research. Furthermore, it meets the minimum standards for social science studies, as established by Dillman *et al.* (2014), ensuring the reliability of the dataset.

The demographic characteristics of the employees who participated in the survey (Cox and Holcomb, 2022) were as follows: based on gender, the majority of respondents were male (54.27%), while females comprised 45.73%. Regarding professional work experience, the largest group (40.70%) had 10–15 years of work experience, followed by those with 5–10 years of experience (33.67%) and those with less than 5 years of experience (14.41%). In addition, 11.22% of the sample had more than 15 years of experience. In terms of the industry sector, 57.12% of the respondents were from the government banking sector, while 42.88% came from the private sector. Finally, in terms of age, the dominant age group was 35–45 years, representing 53.43% of the participants.

3.2 Measures

The items used to measure each variable in the survey were adapted from previous research, including the study by Carpenter *et al.* (2019), Chiu *et al.* (2021), and Lins *et al.* (2024). These items were selected because they have been validated and subjected to various statistical tests for scale development (DeVellis, 2022). A total of 22 relevant questions were identified as suitable for measuring the independent and dependent variables in the proposed model. To assess the adequacy of these items in capturing the essence of each construct, principal components analysis (PCA) was conducted via factor analysis. The validity and reliability of each variable were assessed to confirm the formation of a single factor.

Factor analysis was performed using IBM SPSS 29.0, and the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO-MSA) values were greater than 0.50 for each latent variable, with one component extracted (Finch, 2020; George and Mallery, 2024). We obtained factor-loading values for each item exceeding 0.776, and Cronbach's alpha values for each construct exceeding 0.810 (see Table 2), confirming that these items measure a single factor (Field, 2024; Finch, 2020). Table 2 presents a complete list of the 22 items selected for this study.

The measurement for each variable consisting of perceived self-threat (PST), skepticism (SKP), distrust (DST), anticipated adverse outcomes (AAO), and intention to use AI (IUA), involved multiple items. Respondents were asked to rate these items using a 5-point Likert scale, with 1 indicating "strongly disagree" and 5 indicating "strongly agree."

3.3 Data analysis

Data analysis in this study was conducted using covariance-based structural equation modeling (CB-SEM), an approach designed to test the relationships between unobservable

Table 2. Results of validity and reliability evaluation

Measurement questions	Item	FA	SFL	AVE	MSV	ASV	ω	ρ_c
(A) Perceived Self-Threat (PST) (Source: Adapted from Carpenter et al., 2019)				0.573	0.201	0.163	0.870	0.872
In the financial services industry, AI implementation poses a threat to my job security and professional well-being	PST1	0.831	0.771					
The potential ramifications of AI integration in the financial services workplace pose a direct threat to my career prospects	PST2	0.842	0.850					
AI's presence in our systems poses a significant risk to the stability of my employment in the financial services sector	PST3	0.778	0.690					
The prospect of AI-induced disruptions in my workflow fills me with apprehension	PST4	0.836	0.773					
In the financial services industry, the integration of AI technologies in our systems elevates the inherent risks	PST5	0.776	0.688					
(B) Skepticism (SKP) (Source: Adapted from Lins et al., 2024)				0.732	0.362	0.204	0.932	0.934
I'm doubtful whether AI truly grasps human decision-making complexities, especially in the financial services industry	SKP1	0.925	0.924					
I'm concerned that AI might not handle unique financial situations effectively	SKP2	0.909	0.904					
I'm skeptical that AI systems are transparent and unbiased, especially with sensitive financial data	SKP3	0.850	0.787					
I question AI's ability to empathize with human emotions in financial interactions and decision-making processes	SKP4	0.840	0.768					
I'm skeptical that AI adequately prioritizes privacy and data security in the financial services industry	SKP5	0.902	0.884					
(C) Distrust (DST) (Source: Adapted from Lins et al., 2024)				0.797	0.332	0.223	0.938	0.940
I don't trust the transparency of AI used in the financial services industry	DST1	0.899	0.852					
I don't trust the accountability of AI until specific evidence is provided in the financial services industry	DST2	0.933	0.914					
The use of AI in the financial services industry can lead people to believe things that aren't true	DST3	0.939	0.929					
I do not trust that AI prioritizes privacy and data security in the financial services industry	DST4	0.910	0.873					

(*continued*)

Table 2. Continued

Measurement questions	Item	FA	SFL	AVE	MSV	ASV	ω	ρ_c
(D) Anticipated Adverse Outcomes (AAO) (Source: Adapted from Chiu et al., 2021)				0.654	0.364	0.293	0.906	0.908
I am concerned about the shift in my job responsibilities within the financial services industry following the implementation of AI	AAO1	0.904	0.885					
I am worried about the alteration in decision-making methods within the financial services industry following the implementation of AI	AAO2	0.904	0.887					
I am concerned about my ability to adapt to handling AI systems within the financial services industry	AAO3	0.883	0.824					
I am concerned about the potential decrease in job opportunities for humans within the financial services industry following the implementation of AI	AAO4	0.878	0.768					
I am concerned that AI diminishes the significance and utility of human beings within the financial services industry	AAO5	0.805	0.656					
(E) Intention to use AI (IUA) (Source: Adapted from Chiu et al., 2021)				0.522	0.362	0.270	0.736	0.738
I plan to utilize the AI system in the future within our financial services industry	IUA1	0.902	0.914					
I anticipate using the AI system in the future within our financial services industry	IUA2	0.800	0.539					
I intend to use the AI system in the future within our financial services industry	IUA3	0.851	0.664					

Note(s): FA = factor analysis; SFL = standardized factor loading; AVE = Average variance extracted; MSV = Maximum shared variance; ASV = Average shared variance; ω = McDonald Omega coefficient; ρ_c = Composite reliability
Source(s): Authors' own work

variables. CB-SEM combines confirmatory factor analysis (CFA) and path analysis, making it highly suitable for explanatory-based research (Jöreskog *et al.*, 2016). The CB-SEM estimation process follows several steps, including model specification, identification, fulfillment of various assumptions, and estimation (Kline, 2023; Whittaker and Schumacker, 2022). The primary advantage of this approach is its ability to produce goodness-of-fit (GoF) indices, which allows researchers to evaluate the fit of the model. Additionally, CB-SEM accounts for measurement errors in the model (Gunzler *et al.*, 2021; Hoyle, 2023; Kline, 2023), making it particularly suitable for our study.

4. Results

SmartPLS 4 was used to perform the CB-SEM estimation and obtain the results (Venturini *et al.*, 2023). However, the CB-SEM algorithm in SmartPLS is suitable only for handling non-normal data conditions, utilizing bootstrapping rather than the maximum likelihood (ML) estimator to calculate the standard deviation (STDEV) during model estimation. This method is similar to the asymptotic distribution-free (ADF) estimator. Considering that we used a Likert scale to measure all ordinal variables, achieving multivariate normality was challenging. Therefore, we conducted several preliminary tests, as detailed in the Appendix, to ensure the suitability of the chosen approach. The results of these preliminary tests validated the rationale for using this approach.

Table 3 presents the descriptive statistics for each variable. The calculations showed that the mean values of all latent variables were below five, and the standard deviation (STDEV) values were all below two. According to Cox and Holcomb (2022), these values are within the acceptable ranges. Additionally, the correlation values among the latent variables were below 0.60, with no signs of inverse relationships between the variables. Therefore, we conclude that our main model does not indicate multicollinearity problems (Kalnins and Praitis Hill, 2023). To reinforce this evidence, corrected variance inflation factors (CVIF) were calculated for each independent variable, and no CVIF values were found to be greater than 3, in accordance with the acceptable rule of thumb (see Table 3).

4.1 Evaluation of response biases

To ensure the validity of our main results, we examined two common methodological biases in survey-based research: nonresponse bias (Scheaf *et al.*, 2023) and common method variance (Podsakoff *et al.*, 2024). Based on the extensive tests detailed in the Appendix, we can confidently conclude that these biases do not threaten the validity of our findings.

4.2 Evaluation of validity and reliability

We evaluated the validity and reliability of the measurement items using confirmatory factor analysis (CFA), which included assessments of convergent and divergent validity, McDonald's Omega coefficient (ω), and composite reliability (ρ_c). We also evaluated the GoF of the CFA model to ensure appropriate model fit. Based on the tests detailed in the Appendix, all the measurement items in the model met the criteria for convergent and divergent validity (see Tables 2 and 3) and satisfied the construct reliability thresholds. Additionally, the CFA model demonstrated a satisfactory level of the GoF.

4.3 Evaluation of the full model

Full model assessment and final model estimation were conducted using bootstrapping procedures to handle non-normal data. In total, 10,000 resamples were performed to obtain

Table 3. Results of divergent validity, summary of descriptive statistics, and correlations between latent variables

Latent variable	1	2	3	4	5
Anticipated Adverse Outcomes (AAO)	*(0.85)*	0.531**	−0.597**	0.426**	0.598**
Distrust (DST)	0.567	*(0.85)*	−0.572**	0.396**	0.350**
Intention to use AI (IUA)	0.402	0.658	*(0.85)*	−0.443**	−0.452**
Perceived Self-Threat (PST)	0.402	0.657	0.367	*(0.85)*	0.346**
Skepticism (SKP)	0.642	0.588	0.354	0.416	*(0.85)*
Mean	3.999	4.217	2.210	4.000	3.738
Standard Deviation (STDEV)	0.946	0.827	1.047	0.966	1.109
Corrected Variance Inflation Factor (CVIF)	2.282	1.695	–	2.663	1.933

Note(s): HTMT values below the diagonal. Above the diagonal are correlation values. Diagonal and italic elements are the cut-off values for HTMT. ** The correlation of constructs is significant at the 0.01 level (2-tailed)
Source(s): Authors' own work

stable estimates. Several key metrics were evaluated, including *r*-square (R^2) and effect size (f^2). The proposed model yielded R^2 values of 0.611 and 0.638 for anticipated adverse outcomes (AAO) and intention to use AI (IUA), respectively. According to Cohen *et al.* (2003), these R^2 values are within the acceptable range for social science research. Additionally, to complement the null hypothesis significance tests (NHST), we calculated f^2 values ranging from 0.046 to 0.358, all of which exceeded 0.02. These f^2 values confirm the extent to which the null hypotheses are false, thus supporting the testing of alternative hypotheses (Iacobucci *et al.*, 2023).

4.4 Testing of hypotheses

Hypothesis testing was conducted to assess the acceptance or rejection of the proposed alternative hypotheses using several key parameters: beta coefficient (β), standard deviation (STDEV), *p*-value, and *t*-statistic at a significance level of 5% (one-sided test) following the guidelines provided by Hoyle (2023) and Kline (2023). All beta coefficients (β) were standardized. The results of our hypothesis testing, shown in Table 4 and Figure 2, support our proposed alternative hypotheses. Specifically, our research provides empirical evidence regarding the direct relationship between perceived self-threat (PST), skepticism (SKP), distrust (DST), and intention to use AI (IUA) among banking industry employees. Beta coefficients (β) of −0.252 (STDEV = 0.086) were generated for perceived self-threat (PST), −0.193 (STDEV = 0.037) for skepticism (SKP), and −0.276 (STDEV = 0.062) for distrust (DST), all with $p < 0.01$. Based on these findings and results, we have supported Hypothesis 1a (H1a), Hypothesis 2a (H2a), and Hypothesis 3a (H3a).

Ultimately, we tested the indirect effects of these relationships on anticipated adverse outcomes (AAO). Our analysis showed beta (β) values of −0.317 (STDEV = 0.058) for the indirect effect between PST, AAO, and IUA; −0.088 (STDEV = 0.027) for the indirect effect between SKP, AAO, and IUA; and −0.049 (STDEV = 0.025) for the indirect effect between DST, AAO, and IUA. The significance level of these relationships was indicated by $p < 0.05$. Consequently, we can conclude that our results strongly support Hypothesis 1b (H1b), Hypothesis 2b (H2b), and Hypothesis 3b (H3b).

Table 4. Findings of hypothesis testing

Connection between latent variables	β	STDEV	*p*-value	*t*-statistic	Finding
Direct effect					
Perceived Self-Threat (PST) → Intention to use AI (IUA)	−0.252	0.086	0.002**	2.919**	H1a supported
Skepticism (SKP) → Intention to use AI (IUA)	−0.193	0.037	0.000***	5.156***	H2a supported
Distrust (DST) → Intention to use AI (IUA)	−0.276	0.062	0.000***	4.431***	H3a supported
Indirect effect					
Perceived Self-Threat (PST) → Anticipated Adverse Outcomes (AAO) → Intention to use AI (IUA)	−0.317	0.058	0.000***	5.427***	H1b supported
Skepticism (SKP) → Anticipated Adverse Outcomes (AAO) → Intention to use AI (IUA)	−0.088	0.027	0.001***	3.282***	H2b supported
Distrust (DST) → Anticipated Adverse Outcomes (AAO) → Intention to use AI (IUA)	−0.049	0.025	0.025*	1.954*	H3b supported

Note(s): β = standardized beta coefficient; STDEV = standard deviation; * $|t| \geq 1.65$ at $p < 0.05$ level; ** $|t| \geq 2.33$ at $p < 0.01$ level; *** $|t| \geq 3.09$ at $p < 0.001$ level
Source(s): Authors' own work

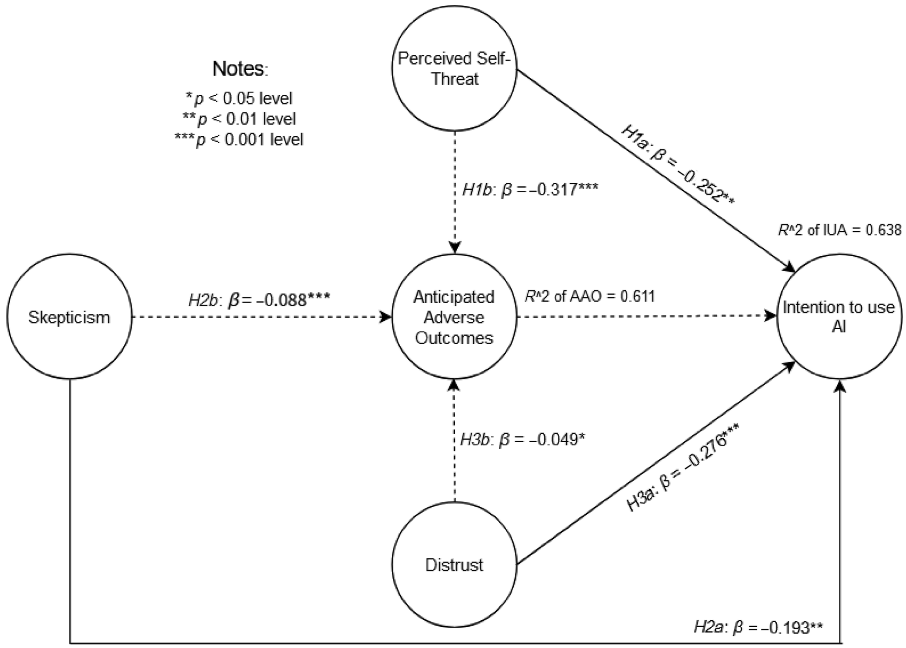

Figure 2. Results of structural equation modeling analysis. **Source:** Authors' own work

4.5 Robustness checks

We assessed endogeneity bias using the Gaussian copula approach, a method that does not require instrumental variables (Park and Gupta, 2012). Separate regression models were conducted to create a "copula term." The output from the Gaussian copula analysis did not reveal statistically significant *p*-values at the 5% level for any regressor model (Eckert and Hohberger, 2022; Park and Gupta, 2012), indicating that our main findings are not affected by endogeneity bias.

5. Discussion

The findings of this study provide critical insights into the barriers that influence employees' intentions to adopt AI in the banking sector. First, our findings illustrate that perceived self-threat significantly negatively affects employees' intention to use AI, both directly and indirectly, through anticipated adverse outcomes. Specifically, employees who perceive high levels of self-threat, such as fear of job displacement or changes in job roles, exhibit notable reluctance to adopt AI technologies (Wong *et al.*, 2024). This is because of their anticipation of adverse outcomes related to AI adoption, which compounds their resistance (Chiu *et al.*, 2021). The direct negative impact of perceived self-threat underscores the importance of addressing employee concerns regarding job security and career stability. The indirect effect, where heightened self-threat perceptions increase anticipation of negative consequences, such as reduced job satisfaction or increased workload, further reinforces the need for targeted communication strategies that emphasize the positive aspects of AI integration and offer support to alleviate these concerns (Chaouali *et al.*, 2024; Presbitero and Teng-Calleja, 2023).

Second, our results reveal that skepticism significantly negatively affects employees' intention to use AI, both directly and indirectly, through anticipated adverse outcomes. Employees who are skeptical about the reliability, effectiveness, and ethical implications of AI are more likely to foresee negative outcomes associated with its use (Lins *et al.*, 2024). This skepticism undermines their confidence in AI, thereby reducing their willingness to engage in these technologies (Chang and Hsiao, 2024). The findings indicate that skepticism not only affects the direct intention to use AI but also amplifies concerns about transparency, accountability, and ethical use. To address this, organizations must focus on demonstrating AI's reliability and ethical standards of AI. Engaging in transparent communication and actively addressing skepticism can help build confidence in AI technologies and mitigate the perceived risks (Aharony *et al.*, 2020; Barari *et al.*, 2024).

Finally, our findings indicate that distrust has a profound negative effect on employee intention to use AI, manifesting both directly and indirectly through anticipated adverse outcomes. Employees who distrust AI are more likely to anticipate negative consequences such as privacy breaches or data misuse, which directly reduces their intention to use AI (Lins *et al.*, 2024; Salem and Rassouli, 2024). Indirectly, this distrust exacerbates the anticipation of adverse outcomes, reinforcing the reluctance to adopt AI (Chiu *et al.*, 2021). Our findings emphasize the critical need for organizations to foster trust in AI through robust security measures, clear ethical guidelines, and transparent practices (Gkinko and Elbanna, 2023; Xu *et al.*, 2024). By addressing issues of distrust and demonstrating commitment to ethical AI deployment, organizations can enhance employee acceptance and facilitate the smoother integration of AI technologies into business operations.

5.1 Theoretical implications

This study advances theoretical understanding by extending Protection Motivation Theory (PMT) to the context of AI adoption in the banking sector, demonstrating how perceived self-threat, skepticism, and distrust influence employees' intentions to use AI. By incorporating these psychological factors into PMT, this study broadens its applicability beyond its traditional focus on health-related behaviors (Khan and Pandey, 2022; Kharbat *et al.*, 2021), emphasizing the role of individual cognitive and emotional responses in technology adoption. These findings highlight the mediating role of anticipated adverse outcomes, illustrating how employees assess potential risks and consequences before adopting AI. This theoretical extension not only reinforces PMT's relevance in organizational technology adoption, but also opens new avenues for exploring the interaction between psychological constructs and resistance to innovation (Park *et al.*, 2024).

5.2 Managerial and policy implications

The findings of this study have important managerial implications for the banking sector, particularly for facilitating AI adoption. Managers must recognize psychological barriers such as perceived self-threat, skepticism, and distrust that employees may experience when integrating AI technologies. Addressing these concerns through proactive communication strategies and support mechanisms can reduce resistance and foster a more positive attitude toward AI adoption. For example, implementing comprehensive training programs that enhance employees' AI-related skills and confidence can alleviate the fear of job displacement and reduce skepticism (Xu *et al.*, 2024). Additionally, establishing clear policies and providing transparent information about AI's role of AI in the organization can build trust and mitigate concerns about potential negative outcomes (Yang *et al.*, 2024).

From a policy perspective, this study underscores the need for regulatory frameworks that address the ethical and practical challenges of AI adoption in the banking sector (Sheth *et al.*, 2022). Policymakers should develop guidelines that promote fairness, accountability, and transparency in AI implementation, ensuring that these technologies do not reinforce biases or compromise employees' job security. Additionally, policies that support continuous professional development and provide resources for skill enhancement can help employees adapt to technological changes, thereby reducing the likelihood of negative outcomes associated with AI adoption (Sheth *et al.*, 2022). By aligning organizational practices with these policy recommendations, both managers and policymakers can facilitate more effective, ethical, and employee-centered integration of AI technologies in the banking industry.

5.3 Limitations and suggestions for future research

As with any research, this study has limitations that need to be acknowledged. First, it may not account for all potential moderating variables such as technology anxiety and risk aversion (Cintamür, 2024). These factors could influence the relationships between the variables observed in our model. Future research should incorporate these variables to provide a more comprehensive analysis. Additionally, examining both the positive and negative aspects of AI adoption could offer a more balanced understanding of employee intentions.

Second, the quantitative approach used in this study relies on a limited number of questions to measure the variables, which may not fully capture the specific barriers to AI adoption. To gain a deeper understanding, future studies could include qualitative methods such as interviews to explore the barriers perceived by employees (Booyse and Scheepers, 2024; Papagiannidis *et al.*, 2023). This approach offers a richer perspective on these relationships and facilitates the triangulation of findings.

Finally, our study primarily employs protection motivation theory (PMT) to explain the relationships between the investigated variables. Future research could explore alternative theoretical frameworks, such as social dominance theory or role theory (Gligor *et al.*, 2021), to provide more nuanced explanations of the observed relationships.

References

Aharony, N., Bouhnik, D. and Reich, N. (2020), “Readiness for information security of teachers as a function of their personality traits and their assessment of threats”, *Aslib Journal of Information Management*, Vol. 72 No. 5, pp. 787-812, doi: 10.1108/ajim-12-2019-0371.

Ali, A., Hameed, A., Moin, M.F. and Khan, N.A. (2023), “Exploring factors affecting mobile-banking app adoption: a perspective from adaptive structuration theory”, *Aslib Journal of Information Management*, Vol. 75 No. 4, pp. 773-795, doi: 10.1108/ajim-08-2021-0216.

Au, W.C.W. and Tsang, N.K.F. (2023), “Gig workers’ self-protective behaviour against legal risks: an application of protection motivation theory”, *International Journal of Contemporary Hospitality Management*, Vol. 35 No. 4, pp. 1376-1397, doi: 10.1108/ijchm-12-2021-1537.

Bandalos, D.L. (2018), *Measurement Theory and Applications for the Social Sciences*, Guilford Press, New York.

Barari, M., Casper Ferm, L.-E., Quach, S., Thaichon, P. and Ngo, L. (2024), “The dark side of artificial intelligence in marketing: meta-analytics review”, *Marketing Intelligence & Planning*, Vol. 42 No. 7, pp. 1234-1256, doi: 10.1108/mip-09-2023-0494.

Booyse, D. and Scheepers, C.B. (2024), “Barriers to adopting automated organisational decision-making through the use of artificial intelligence”, *Management Research Review*, Vol. 47 No. 1, pp. 64-85, doi: 10.1108/mrr-09-2021-0701.

Byrne, B.M. (2016), *Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming*, Routledge, New York.

Carpenter, D., Young, D.K., Barrett, P. and McLeod, A.J. (2019), “Refining technology threat avoidance theory”, *Communications of the Association for Information Systems*, Vol. 44 No. 1, pp. 380-407, doi: 10.17705/1cais.04422.

Chang, T.-S. and Hsiao, W.-H. (2024), “Understand resist use online customer service chatbot: an integrated innovation resist theory and negative emotion perspective”, *Aslib Journal of Information Management*., doi: 10.1108/ajim-12-2023-0551.

Chaouali, W., Souiden, N., Aloui, N., Ben Dahmane Mouelhi, N., Woodside, A.G. and Ben Abdelaziz, F. (2024), “Roles of barriers and gender in explaining consumers’ chatbot resistance in banking: a fuzzy approach”, *International Journal of Bank Marketing*, Vol. 42 No. 7, pp. 1867-1887, doi: 10.1108/ijbm-03-2023-0153.

Chiu, Y.-T., Zhu, Y.-Q. and 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*, Vol. 60, 102379, doi: 10.1016/j.ijinfomgt.2021.102379.

Cintamür, İ.G. (2024), "Acceptance of artificial intelligence devices in banking services: moderation role of technology anxiety and risk aversion", *International Journal of Bank Marketing*, Vol. 42 No. 7, pp. 2143-2176, doi: 10.1108/IJBM-10-2023-0563.

Cohen, J., Cohen, P., West, S.G. and Aiken, L.S. (2003), *Applied Multiple Regression/correlation Analysis for the Behavioral Sciences*, Lawrence Erlbaum Associates, Mahwah, NJ.

Cox, K.S. and Holcomb, Z.C. (2022), *Interpreting Basic Statistics: A Workbook Based on Excerpts from Journal Articles*, Routledge, New York.

DeVellis, R.F. (2022), *Scale Development: Theory and Applications*, Sage Publications, Thousand Oaks.

Dillman, D.A., Smyth, J.D. and Christian, L.M. (2014), *Internet, Phone, Mail, and Mixed Mode Surveys: The Tailored Design Method*, Wiley, Hoboken, NJ.

Eckert, C. and Hohberger, J. (2022), "Addressing endogeneity without instrumental variables: an evaluation of the Gaussian Copula approach for management research", *Journal of Management*, Vol. 49 No. 4, pp. 1460-1495, doi: 10.1177/01492063221085913.

Field, A. (2024), *Discovering Statistics Using IBM SPSS Statistics*, Sage Publications, Thousand Oaks.

Finch, W.H. (2020), *Exploratory Factor Analysis*, SAGE Publications, Thousand Oaks.

Gamble, A. (2020), "Artificial intelligence and mobile apps for mental healthcare: a social informatics perspective", *Aslib Journal of Information Management*, Vol. 72 No. 4, pp. 509-523, doi: 10.1108/ajim-11-2019-0316.

George, D. and Mallery, P. (2024), *IBM SPSS Statistics 29 Step by Step: A Simple Guide and Reference*, Routledge, New York.

Gkinko, L. and Elbanna, A. (2023), "Designing trust: the formation of employees' trust in conversational AI in the digital workplace", *Journal of Business Research*, Vol. 158, 113707, doi: 10.1016/j.jbusres.2023.113707.

Gligor, D.M., Pillai, K.G. and Golgeci, I. (2021), "Theorizing the dark side of business-to-business relationships in the era of AI, big data, and blockchain", *Journal of Business Research*, Vol. 133, pp. 79-88, doi: 10.1016/j.jbusres.2021.04.043.

Gunzler, D.D., Perzynski, A.T. and Carle, A.C. (2021), *Structural Equation Modeling for Health and Medicine*, CRC Press, Boca Raton.

Henseler, J. (2021), *Composite-based Structural Equation Modeling: Analyzing Latent and Emergent Variables*, Guildford Press, New York.

Hoyle, R.H. (Ed.) (2023), *Handbook of Structural Equation Modeling*, Guilford Press, New York.

Iacobucci, D., Popovich, D.L., Moon, S. and Román, S. (2023), "How to calculate, use, and report variance explained effect size indices and not die trying", *Journal of Consumer Psychology*, Vol. 33 No. 1, pp. 45-61, doi: 10.1002/jcpy.1292.

Jöreskog, K.G., Olsson, U.H. and Wallentin, F.Y. (2016), *Multivariate Analysis with LISREL*, Springer, Cham, Switzerland.

Kalnins, A. and Praitis Hill, K. (2023), "The VIF score. What is it good for? Absolutely nothing", *Organizational Research Methods*, Vol. 28 No. 1, pp. 58-75, doi: 10.1177/10944281231216381.

Kamoonpuri, S.Z. and Sengar, A. (2023), "Hi, May AI help you? An analysis of the barriers impeding the implementation and use of artificial intelligence-enabled virtual assistants in retail", *Journal of Retailing and Consumer Services*, Vol. 72, 103258, doi: 10.1016/j.jretconser.2023.103258.

Khan, A.W. and Pandey, J. (2022), "Dark side consequences of cyberchondria: an empirical investigation", *Aslib Journal of Information Management*, Vol. 74 No. 5, pp. 801-817, doi: 10.1108/ajim-08-2021-0222.

Kharbat, F.F., Alshawabkeh, A. and Woolsey, M.L. (2021), "Identifying gaps in using artificial intelligence to support students with intellectual disabilities from education and health perspectives", *Aslib Journal of Information Management*, Vol. 73 No. 1, pp. 101-128, doi: 10.1108/ajim-02-2020-0054.

Kline, R.B. (2023), *Principles and Practice of Structural Equation Modeling*, Gulford Press, New York.

Kumar, G., Singh, R.K., Arya, V. and Mishra, S.K. (2024), "Analyzing barriers in adoption of artificial intelligence for resilient health care services to society", *Global Journal of Flexible Systems Management*, Vol. 25 No. 1, pp. 179-197, doi: 10.1007/s40171-024-00373-4.

Labrecque, L.I., Peña, P.Y., Leonard, H. and Leger, R. (2024), "Not all sunshine and rainbows: exploring the dark side of AI in interactive marketing", *The Journal of Research in Indian Medicine*, Vol. 18 No. 5, pp. 970-999, doi: 10.1108/jrim-02-2024-0073.

Lin, R.-R. and Lee, J.-C. (2024), "The supports provided by artificial intelligence to continuous usage intention of mobile banking: evidence from China", *Aslib Journal of Information Management*, Vol. 76 No. 2, pp. 293-310, doi: 10.1108/ajim-07-2022-0337.

Lins, S., Greulich, M., Löbbers, J., Benlian, A. and Sunyaev, A. (2024), "Why so skeptical? Investigating the emergence and consequences of consumer skepticism toward web seals", *Information & Management*, Vol. 61 No. 2, 103920, doi: 10.1016/j.im.2024.103920.

Litman, L. and Robinson, J. (2021), *Conducting Online Research on Amazon Mechanical Turk and beyond*, SAGE Publications, Thousand Oaks.

Manser Payne, E., Peltier, J.W. and Barger, V.A. (2018), "Mobile banking and AI-enabled mobile banking", *The Journal of Research in Indian Medicine*, Vol. 12 No. 3, pp. 328-346, doi: 10.1108/jrim-07-2018-0087.

Manser Payne, E.H., Peltier, J. and Barger, V.A. (2021), "Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms", *The Journal of Research in Indian Medicine*, Vol. 15 No. 1, pp. 68-85, doi: 10.1108/jrim-10-2020-0214.

Miller, B.K. and Simmering, M.J. (2023), "Attitude toward the color blue: an ideal marker variable", *Organizational Research Methods*, Vol. 36 No. 3, pp. 409-440, doi: 10.1177/10944281221075361.

Northey, G., Hunter, V., Mulcahy, R., Choong, K. and Mehmet, M. (2022), "Man vs machine: how artificial intelligence in banking influences consumer belief in financial advice", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1182-1199, doi: 10.1108/ijbm-09-2021-0439.

Omoge, A.P., Gala, P. and Horky, A. (2022), "Disruptive technology and AI in the banking industry of an emerging market", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1217-1247, doi: 10.1108/ijbm-09-2021-0403.

Papagiannidis, E., Mikalef, P., Conboy, K. and Van de Wetering, R. (2023), "Uncovering the dark side of AI-based decision-making: a case study in a B2B context", *Industrial Marketing Management*, Vol. 115, pp. 253-265, doi: 10.1016/j.indmarman.2023.10.003.

Park, S. and Gupta, S. (2012), "Handling endogenous regressors by joint estimation using copulas", *Marketing Science*, Vol. 31 No. 4, pp. 567-586, doi: 10.1287/mksc.1120.0718.

Park, J., Yun, J. and Chang, W. (2024), "Intention to adopt services by AI avatar: a protection motivation theory perspective", *Journal of Retailing and Consumer Services*, Vol. 80, 103929, doi: 10.1016/j.jretconser.2024.103929.

Pielsticker, D.I. and Hiebl, M.R.W. (2020), "Survey response rates in family business research", *European Management Review*, Vol. 17 No. 1, pp. 327-346, doi: 10.1111/emre.12375.

Podsakoff, P.M., Podsakoff, N.P., Williams, L.J., Huang, C. and 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*, Vol. 11 No. 1, pp. 17-61, doi: 10.1146/annurev-orgpsych-110721-040030.

Presbitero, A. and Teng-Calleja, M. (2023), "Job attitudes and career behaviors relating to employees' perceived incorporation of artificial intelligence in the workplace: a career self-management perspective", *Personnel Review*, Vol. 52 No. 4, pp. 1169-1187, doi: 10.1108/pr-02-2021-0103.

Rahman, M., Ming, T.H., Baigh, T.A. and Sarker, M. (2023), "Adoption of artificial intelligence in banking services: an empirical analysis", *International Journal of Emerging Markets*, Vol. 18 No. 10, pp. 4270-4300, doi: 10.1108/ijoem-06-2020-0724.

Rana, N.P., Chatterjee, S., Dwivedi, Y.K. and 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*, Vol. 31 No. 3, pp. 364-387, doi: 10.1080/0960085x.2021.1955628.

Rautiainen, A., Scapens, R.W., Järvenpää, M., Auvinen, T. and Sajasalo, P. (2024), "Towards fluid role identity of management accountants: a case study of a Finnish bank", *The British Accounting Review*, Vol. 56 No. 4, 101341, doi: 10.1016/j.bar.2024.101341.

Raykov, T. and Marcoulides, G.A. (2011), *Introduction to Psychometric Theory*, Routledge, New York.

Roos, J.M. and Bauldry, S. (2022), *Confirmatory Factor Analysis*, SAGE Publications, Thousand Oaks.

Salem, M.Z. and Rassouli, A. (2024), "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*, Vol. 35 No. 2, pp. 391-408, doi: 10.1108/cr-12-2023-0309.

Scheaf, D.J., Loignon, A.C., Webb, J.W. and Heggestad, E.D. (2023), "Nonresponse bias in survey-based entrepreneurship research: a review, investigation, and recommendations", *Strategic Entrepreneurship Journal*, Vol. 17 No. 2, pp. 291-321, doi: 10.1002/sej.1453.

Sheth, J.N., Jain, V., Roy, G. and Chakraborty, A. (2022), "AI-driven banking services: the next Frontier for a personalised experience in the emerging market", *International Journal of Bank Marketing*, Vol. 40 No. 6, pp. 1248-1271, doi: 10.1108/ijbm-09-2021-0449.

Soral, P., Pati, S.P. and Kakani, R.K. (2022), "Knowledge hiding as a coping response to the supervisors' dark triad of personality: a protection motivation theory perspective", *Journal of Business Research*, Vol. 142, pp. 1077-1091, doi: 10.1016/j.jbusres.2021.12.075.

Spherical Insights (2024), "Artificial intelligence in banking market size report, 2033".

Vasiliu, V. and Yavetz, G. (2024), "Who's afraid of AI? Socio-technological perspectives on artificial intelligence in the workforce: an Israeli case study", *Aslib Journal of Information Management* doi: 10.1108/ajim-12-2023-0562.

Venturini, S., Mehmetoglu, M. and Latan, H. (2023), "Software packages for partial least squares structural equation modeling: an updated review", in Latan, H., Hair, J.F. and Noonan, R. (Eds), *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications*, 2nd ed., Springer, Cham, pp. 113-152.

Whittaker, T.A. and Schumacker, R.E. (2022), *A Beginner's Guide to Structural Equation Modeling*, Routledge, New York.

Wong, L.-W., Tan, G. W.-H., Ooi, K.-B. and Dwivedi, Y. (2024), "The role of institutional and self in the formation of trust in artificial intelligence technologies", *Internet Research*, Vol. 34 No. 2, pp. 343-370, doi: 10.1108/intr-07-2021-0446.

Xu, Y., Huang, Y., Wang, J. and Zhou, D. (2024), "How do employees form initial trust in artificial intelligence: hard to explain but leaders help", *Asia Pacific Journal of Human Resources*, Vol. 62 No. 3, e12402, doi: 10.1111/1744-7941.12402.

Yang, J., Blount, Y. and Amrollahi, A. (2024), "Artificial intelligence adoption in a professional service industry: a multiple case study", *Technological Forecasting and Social Change*, Vol. 201, 123251, doi: 10.1016/j.techfore.2024.123251.

(The Appendix follows overleaf)

Appendix

Preliminary testing

Several preliminary tests were conducted before the main analysis. First, we assessed the multivariate normality using the Cramér–von Mises test. The results showed statistically significant skewness and kurtosis values at the 5% significance level, indicating that the data distribution was not normal (Byrne, 2016; Kline, 2023). Second, we checked for outliers in our observations by examining the *Z*-score values and found no cases with values higher than 2.58, according to the rule of thumb (Field, 2024; George and Mallery, 2024). Finally, to assess heteroscedasticity in our observations, we used the chi-squared test. Our results did not detect a significant residual variance at the 5% significance level, confirming that the homoscedasticity assumption was met.

Response bias testing

Following the guidelines of Scheaf *et al.* (2023), we conducted a multivariate analysis of variance (MANOVA) to assess the potential for nonresponse bias across demographic variables. The results showed no statistically significant differences in the main variables based on the demographic categories at the 5% significance level. To further support this finding, *t*-tests were performed to compare early and late survey responses (Scheaf *et al.*, 2023). Again, no significant differences were found between the two groups. Based on these results, we conclude that non-response bias did not affect the data collection process and that our main findings remain representative of the entire sample.

Furthermore, following the recommendations of Podsakoff *et al.* (2024), we examined common method variance (CMV) using a marker variable approach, as described by Miller and Simmering (2023). Initially, we mitigated CMV through a survey design by separating independent and dependent variables. Following Miller and Simmering (2023) guidelines, we introduced a marker variable in our survey that was unrelated to the focal constructs in the model. This marker variable was then evaluated using the correlation coefficient and model fit by comparing models with and without the marker variable. The marker variable did not have a significant correlation ($p > 0.05$) with the focal constructs in the model. Additionally, the CFA marker model produced a worse fit than the main CFA model did. Considering these two results, we concluded that CMV did not pose a threat to our survey and did not introduce bias into our main results.

Validity and reliability testing

The main CFA model was used to evaluate the convergent validity, divergent validity, and reliability of the constructs. Convergent validity was tested using standardized factor loadings (SFL) and average variance extracted (AVE), whereas divergent validity was assessed using the heterotrait-monotrait ratio (HTMT), maximum shared variance (MSV), and average shared variance (ASV). In Table 2, all items show SFL values above 0.656, and AVE values exceed 0.522 for all constructs, except IUA2, which, although slightly lower at 0.539, is still acceptable; thus, convergent validity meets the rule of thumb (Bandalos, 2018; Roos and Bauldry, 2022). Additionally, the HTMT ratio yielded values below 0.85, and the MSV and ASV values were smaller than the AVE values, as shown in Tables 2 and 3. Based on these results, it can be concluded that divergent validity meets the rule of thumb (Henseler, 2021).

Construct reliability was evaluated using McDonald's Omega coefficient (ω) and composite reliability (ρ_c). It is recommended that both measures have values greater than 0.70 (Raykov and Marcoulides, 2011). As Table 2 shows, our results indicate that both coefficients exceed 0.736, confirming the reliability of the constructs in our measurements. Additionally, the goodness-of-fit (GoF) indices generated by our main CFA model are as follows: minimum discrepancy function divided by the degrees of freedom (CMIN/DF) = $0.000 < 0.05$; Comparative Fit Index (CFI) = $0.924 > 0.90$; Normed Fit Index (NFI) = $0.938 > 0.90$; Goodness-of-Fit Index (GFI) = $0.907 > 0.85$; Parsimony Goodness-of-Fit Index (PGFI) = $0.669 > 0.60$; and Root Mean Square Error of Approximation (RMSEA) = $0.064 < 0.08$ (Jöreskog *et al.*, 2016; Kline, 2023; Whittaker and Schumacker, 2022). Based on these results, the model demonstrated good fit.

About the authors

Ahyar Yuniawan currently holds the position of Associate Professor at Diponegoro University in Semarang, Indonesia. He has authored numerous articles indexed in Scopus and Web of Science (WOS). Ahyar Yuniawan is the corresponding author and can be contacted at: ahyar_y@live.undip.ac.id

Hersugondo Hersugondo currently holds the position of Associate Professor at Diponegoro University in Semarang, Indonesia. He has authored numerous articles indexed in Scopus and Web of Science (WOS).

Fuad Mas'ud currently holds the position of Associate Professor at Diponegoro University in Semarang, Indonesia. He has authored numerous articles indexed in Scopus and Web of Science (WOS).

Hengky Latan currently serves as Research Director at the FTD Institute and Senior Researcher at HLC Consulting, Indonesia. With a prolific academic career, he has authored over 15 books and more than 65 articles, published in leading international journals and by renowned publishers. Recognized among the top 2% of most-cited scientists globally by Stanford University since 2021, his scholarly work has amassed over 22,000 citations (H-index = 55), showcasing his exceptional contributions within just a decade.

Murad Ali is Assistant Professor at Newcastle Business School, Northumbria University, UK. His main research interest is in the advancement of research methods to further the understanding of human resource management, knowledge management, innovation, and sustainability. His approach is interdisciplinary, and he has published articles in top-tier journals recognized by major academic rankings (FT50, CNRS, CABS4), with his work receiving several best paper awards. He has also been an editorial board member of the *Journal of Business Research*.

Moacir Godinho Filho is a Full Professor of Supply Chain Management, Operations Management, and Decision Sciences at EM Normandie Business School, France. His research interests include supply chain management, operations management, sustainable operations, industry 4.0, production planning and control, lean manufacturing, and quick response manufacturing. He has published more than 170 papers in journals with highly selective editorial standards, most of which have high impact factors in the operations management field (JCR by Thomson Reuters) and are indexed in the ABS and FNEGE rankings.