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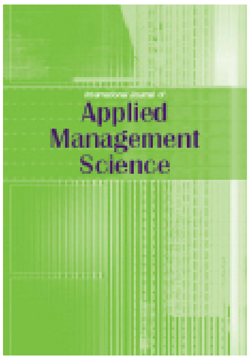

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Quang Hung Do

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The analysis of critical success factor ranking for artificial intelligence adoption in banking sector using fuzzy analytic hierarchy process

Quang Hung Do

Posts and Telecommunications Institute of Technology (PTIT),
Ha Dong District, Hanoi, Vietnam
Email: dqhung@ptit.edu.vn
Email: quanghung.fcu@gmail.com

Abstract: Artificial intelligence applications in the banking industry have attracted a lot of interest. The paper examined the critical success factors influencing artificial intelligence adoption which have been identified from the literature survey and through experts' opinions have finally been confirmed in context of this study on banking organisations. Further, fuzzy Analytic Hierarchy Process (AHP) has been used to evaluate the identified 15 critical factors and to find their priorities in banking organisations. Moreover, a conceptual framework based on Technology Organisation Environment Human (TOEH) theory was utilised in the context of the Vietnamese bank sector. The results of the study indicate that banking users' trust, regulatory environment and security and privacy are the most significant critical success factors for adopting artificial intelligence in banking. This paper contributes to the understanding of artificial intelligence, its features and highlights the importance of new technology and solutions in the banking sector.

Keywords: banking sector; artificial intelligence adoption; critical success factors; fuzzy analytic hierarchy process; Vietnam.

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Biographical notes: Quang Hung Do is an Associate Professor currently with Posts and Telecommunications Institute of Technology (PTIT), Vietnam. Previously, He was an Associate Professor and the Vice Dean in the Department of Information Technology at University of Transport Technology (UTT, Vietnam). He has published more than ninety papers in academic journals, conferences and edited books. He was a Program Committee and served as the Chair for various international conferences. He has also served as a Reviewer of several journals, such as, *Applied Soft Computing*, *Journal of the Operational Research Society*, *Iranian Journal of Fuzzy Systems* and *Concurrent Engineering: Research and Applications*. His research interests include artificial intelligence techniques (i.e., neural networks and neuro-fuzzy systems), machine learning, fuzzy method, information systems, AI application in business, management and finance.

1 Introduction

Artificial Intelligence (AI) is a simulation of human intelligence that aids in the development of better computers that can carry out human tasks in an intelligent manner. Like a human brain, AI can make decisions and think better based on the information provided to it. In the current economy, artificial intelligence is growing more and more prevalent. AI-based techniques have shown to be effective and useful in recent years. The benefits of AI-based solutions include accelerating the analysis of information, producing more precise and reliable data outputs, and enabling employees to do challenging tasks. AI applications in banking may be grouped into several major groups: 1) customer-focused front office applications (voice assistants and biometrics), 2) operations-focused back-office applications (credit underwriting with smart contracts infrastructure), 3) trading and portfolio management and 4) regulatory compliance (Fares et al., 2022; Kaya et al., 2019).

In Vietnam, people have been favouring the trend of digital transformation and the implementation of AI technologies over the past few years. The advancement of science and technology has altered how the younger generation of customers, who are accustomed to digital services, approach banking and financial services, constantly looking for better service and personalised experiences. The COVID-19 epidemic serves as an incentive, accelerating the proactive implementation of revolutionary technical solutions in the banking sector. AI applications foster innovation, reduce costs and enhance products and services, which benefits and adds value for both customers and financial institutions. The promise of developing AI applications in the financial and banking industry is very high given the current industrialisation and modernisation conditions in Vietnam, which will assist to increase the effectiveness of the innovation process. Additionally, due to the effects of the integration process, international banks and financial intermediary organisations are fierce competitors for Vietnamese commercial banks. Applications of AI are currently playing a significant role in improving banks' operating efficiency, agility and competitive advantages. However, compared to other nations in the region and the world, Vietnam is still very early in the development of AI and its application in the financial and banking industry and has several limitations (Trung et al., 2023). Moreover, academics have increasingly focused on the deployment of AI technology in organisations in recent years (Baabdullah et al., 2021; Chatterjee et al., 2021; Pelau et al., 2021). Fewer studies have focused on the determinants of AI adoption performance in comparison to previous research that has investigated the antecedents of AI adoption inside organisations. Even though there has lately been research on the several characteristics of AI adoption in banking. While many aspects of AI adoption were covered by these academics, there is still a lack of study on crucial success factors related to AI adoption in banking and related organisational difficulties, particularly in the context of Vietnam. Furthermore, there are not many case studies detailing organisations' actual experiences using AI. This gap in the research poses problems for banks, because the limitations in relation to this area usually mean difficulties for them in planning and implementing AI. The purpose of this work is to fill in some of these gaps in the existing literature. To fulfil this gap, this study employs the Technology-Organisation-Environment-Human (TOEH) model to identify technological, organisational, environmental and human factors influencing the performance of AI adoption in the banking sector, as well as the relative importance of these factors. Here, we systematically analyse the past and current state of AI and banking literature to identify and evaluate the critical factors that most influence the successful implementation of AI in Vietnamese banking sector. In light of this, we aim to address the following research questions:

1 What are the factors that emerge from prior literature regarding the adoption of AI in the banking industry?

2 What are the critical success factors in implementation of AI in Vietnamese banking sector?

In this study, Fuzzy Analytic Hierarchy Process (FAHP) method is used to determine the rank of factors. Analysing a set of options that have been characterised in terms of some evaluative criteria is a significant component of decision-making. Alternatives must be ranked to determine the best alternative or establish the relative importance of each alternative. The Analytic Hierarchy Process (AHP), Technique for Ordering Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organisation Method for Enrichment Evaluation (PROMETHEE) and Elimination and Choice Translating Reality (ELECTRE) are some of the main techniques that assist multiple-criteria decision-making. The AHP technique is out among them as a method that has been widely used to address a variety of complicated decision-making issues. In the AHP, each alternative is compared with every other alternative in terms of the relative importance of its contribution to the criterion under consideration (Garg et al., 2012). Crisp values are used to represent the pairwise comparisons. The pairwise comparison matrix is created by repeating the comparison for each criterion. The pairwise comparison matrix can be used to determine the weight vector. However, when dealing with the uncertainty in the decision-making process, the pure AHP technique usually performs inadequately. As a result, FAHP was developed to address the problems with ambiguity. Since its introduction, the fuzzy AHP approach has been widely applied by numerous academics to address diverse decision-making issues in a variety of fields. Fuzzy AHP was utilised to identify, examine and prioritise the most critical challenges in the software industry and electronic marketplaces (Awan et al., 2022; Fu et al., 2006). By considering risk considerations, Chan and Kumar (2007) provided a fuzzy extended AHP approach for choosing the best supplier. Fuzzy AHP was utilised by Huang et al. (2008) to choose government-sponsored R&D projects. A fuzzy AHP-based framework was proposed by Li et al. (2023) to analyse the main factors and sub-factors of green finance. Fuzzy AHP was also used by Chou et al. (2012) to assess how each criterion in human resource for science and technology was weighted.

Our research focuses on identifying the rank of critical success factors with fair and objective attribute weights. The framework for the utilisation of fuzzy AHP in group MCDM is proposed to achieve high consensus in determining the weights of factors. To calculate the factor weights influencing artificial intelligence adoption in banking sector, the fuzzy AHP approach (Buckley, 1985; Buckley et al., 2001) is used in the study. The study provides a review of the literature to investigate the CSFs affecting the adoption of AI. The AI theoretical model that is being developed is for a cutting-edge banking technology. This work addresses the need for more research and empirical studies on intelligent automation in the banking sector by offering a conceptual model for AI adoption. The results can be used by academics to look at several new advanced technology adoption strategies in the banking industry. Researchers may utilise this finding to look into the factors that affect the adoption of AI in the banking industry further and to produce reliable literature in other industries.

The rest of this paper is organised as follows. Section 2 briefly presents the AI in baking sector and the critical success factors for AI adoption in banking. Section 3 presents the method to identify essential factors. Section 4 presents the empirical and discussion results. Finally, the conclusions with theoretical and managerial contributions and the limitation and further research are presented in Section 5.

2 Literature review

2.1 Artificial intelligence in banking

According to Purdy and Daugherty (2016), by 2027, 23% of the financial employment market would have altered, with AI playing a critical role in improving efficacy and automating processes. Several AI applications in banking are as follows:

- AI is being tested for fraud detection and prevention in online banking. Credit card fraud has been one of the most common types of cybercrime in recent years, which has been compounded by the rapid growth of online and mobile payments. AI algorithms analyse the plausibility of clients' credit card transactions in real time and compare new transactions with prior amounts and locations to detect fraudulent behaviour. If AI detects a risk, it will block the transaction.
- AI is also being tested in Know Your Client processes to verify client identity. AI algorithms scan client documents and assess the accuracy of the information provided by comparing it to data from other sources. If AI algorithms detect irregularities, they raise a red flag, and a more thorough Know Your Client check is undertaken by bank staff.
- Chatbots, often known as virtual assistants, are innovative tools developed to make human-computer interaction easier. Chatbots are examples of artificial intelligence in banking that are replacing front-desk scenes at banks. These AI-powered robots give clients with next-generation digital and personalised interactive experiences.
- Artificial Intelligence (AI) applications enable institutions to analyse all client data to which they have access, learning about their preferences and, as a result, providing customised goods and services matched to customer demands while improving user experience (Fernández, 2019).
- Since AI adoption has enormous potential in the banking industry, this study seeks to make strong theoretical and empirical contributions about AI adoption in the banking sector. The present literature has mostly focused on the application and benefits of AI in banking and has not adequately investigated the key feature of AI-based data exchange facilitation for enhancing overall bank industry efficiency. According to the AI on banking literature, crucial success factors that could impact and determine AI adoption in the banking industry have not been thoroughly studied.

2.2 The critical success factors for AI adoption in banking sector

Owing to the universality of AI and the lack of research on AI adoption at the organisational level, it is problematic to build directly on current theories. AI adoption is a challenging endeavour that requires not only the purchase of technological devices and software, but also the provision of necessary infrastructure and resources over an extended period. As a result, the adoption and application of AI and new technology is one of the top priorities of researchers and practitioners worldwide (Dora et al., 2022). The Technology Acceptance Model (TAM) is a theoretical framework in which various external factors shape users' perceptions of the usefulness and ease of use of new technology, and those factors influence whether users embrace a new technology as well as their attitudes toward it (Davis, 1989). There are no restrictions in the TAM on what external factors may influence the user's perceptions. Meanwhile, the Technology Organisation Environment (TOE) framework presents three contexts that may affect an organisation's information technology adoption process in terms of external variables: technological, organisational and environmental (Tornatzky et al., 1990). While this framework was appropriate for understanding technological acceptance and dissemination from an organisational standpoint, TOE has been widely used in corporation research (Aboelmaged, 2014a; Lian et al., 2014; Liu and Deng, 2015; Na et al., 2022). Moreover, the theoretical HOT fit model was developed using views on technology adoption (Yusof et al., 2006). The model integrates human, organisational and technological factors, as well as their characteristics, holistically. The three dimensions interact and influence one other through their bi-party relationships, namely the Human organisational fit, Human technological fit, and Organisational technological fit, and hence have an impact on the overall Human organisational technological fit. Fit is defined here as the congruence or matching of several elements. Fit is a state that can be perceived or evaluated in a variety of manners. In this study, the adoption and application of AI in the banking sector are investigated using the TOEH fit frameworks' technological, environmental, organisational and human lenses.

The technological factors encompass all technologies supported within and outside the organisation, as well as processes and equipment that highlight innovation characteristics or factors used in technology adoption research. These elements show the organisation's ability to accept new technology and the applicability of current technology (Gangwar et al., 2015). In this study, technological factors include technology readiness, technology complexity, compatibility, relative advantage and security and privacy since they are highly significant and represent the most frequently utilised features in earlier research.

In this context, technology readiness is mentioned as a key factor, which relates to an organisation's ability to adopt new technologies. Technology readiness refers to how organisations are prepared to implement AI technologies. The perceived difficulty of using a certain technology is referred to as technological complexity. Greater difficulty demotivates organisations to acquire new knowledge, reducing their absorptive potential to innovate. As a result, technology complexity is likely to limit innovation. This element has frequently been noted as one of the primary impediments in AI publications and has been identified as an essential determinant in prior investigations. Obstacles include outdated legacy systems and fragmented information systems (Bowen and Morosan, 2018; Thomas and Rajeev, 2018). As a result, complexity is likely to hinder inventive behaviours.

Another critical element addressed in the technological context is compatibility, which underlines how AI adoption fits the adopter's values, experience and needs. A better fit between the technology and the task will result in higher levels of adoption and use. When AI is implemented, new requirements will arise. To be successful, the company's business procedures must be changed to meet new requirements (Alsheibani et al., 2020; Mishra and Pani, 2021). In general, relative advantage relates to the extent to which an organisation may benefit from innovation. Benefits encourage organisations to acquire new knowledge, increasing their willingness to absorb new technologies. As a result, relative advantage appears to contribute to higher levels of technological adoption. The perceived utility of AI to financial businesses is indicated by relative advantage. AI is anticipated to provide a variety of useful benefits ranging from strategic motivation to operational advantages (Tussyadiah, 2020). Furthermore, security and privacy concerns may foster and promote the usage of AI in the banking sector.

The characteristics of an organisation, such as organisational structure, organisational culture, organisation size and the availability of internal resources, are referred to as organisational context. Regarding organisational Factors, we focus on the most common proxies of organisational context in this study: firm size, organisational culture, management support and available resources.

The size of an organisation in terms of staff and budget is referred to as its organisational size. Because of their substantial number of resources, large corporations have an advantage in the early stages of technology adoption (Alsheibani et al., 2018). Organisational culture, a critical organisational component, is significant in AI adoption in banking since it promotes expressions and ideas for systems and procedures in organisations. AI can be considered an innovative technology that has the potential to change the company's business model and systems. As a result, the organisation must be able to adapt to this change. This includes employees who are willing to use new technology in the future. Innovative cultures are more likely to accept AI technologies because they have a passion for and willingness to exploit new, opportunistic ideas. Employees who are constantly eager to learn and develop will aid in the adoption and utilisation of AI technologies. Employees with a creative mentality are more open to adopting new technologies and are better able to find and accept opportunities for AI applications (Lee et al., 2019; Mikalef and Gupta, 2021; Pumplun et al., 2019). Strong support from management is an essential factor in the usage of AI in banking since it ensures that organisations can effectively handle the difficulties associated with cutting-edge technology and thus increase their adoption rate. Management support, it is believed, may increase comprehensive organisational performance, such as sustainability, growth and internationalisation. Furthermore, it conveys an important message to employees that the AI-induced changes are significant and beneficial, making them more motivated to study and adopt AI technology (Diansari et al., 2020; Lo and Fu, 2016). As technological infrastructure, electronic databases, and sufficient human resources with acceptable technology expertise and company resources are important for the effective deployment of AI in banking, establishing sufficient capabilities and resources is a significant factor.

Regarding environmental factors, the industry, competitors, regulations and interactions with the government are all part of the external environment. The role of institutional contexts in defining organisational structure and behaviours is emphasised by institutional theory. The external environment can both encourage and discourage enterprises from adopting new technologies. External isomorphic pressures from the government, competitors and customers are likely to motivate firms to adopt and employ AI. In this study, we focus on regulatory environment (government involvement), competitive pressure and vendor partnership.

Regulatory environment is another factor that highlights the important role of the government in banking organisations for adopting technologies such as AI and blockchain. The regulatory environment refers to government regulations that influence the diffusion of technology. Depending on the nature of the constraints, the regulatory environment may either assist or constrain a company's technical innovation (Agrawal et al., 2019). Companies are more likely to adopt new technology if the regulatory environment favours it. The regulatory environment is one of the most powerful factors influencing the adoption of technology, particularly in developing countries. Because AI is a new technology, government regulation and guidance are critical in governing its application and adoption. As a disruptive technology with several implications, AI raises numerous challenges such as security, privacy and social ethics. As a result, AI requires a well-legislated or regulated environment. As a result, national-level overall planning and AI laws can foster the beneficial development of the AI industry. Furthermore, because AI is revolutionising practically every aspect of human life and society, governments all over the world have committed significant resources to investing in the technology and have produced national level AI development plans and strategies. The government's assistance creates an advantageous environment for AI and will accelerate the spread and impacts of AI (Nwafor, 2021; Pan et al., 2022).

Competitive pressure drives technological innovation. Adopting new technology is frequently a strategic necessity in order to compete in the market. It is stated that IT innovation has the potential to change the industry structure, alter competition rules, leverage new approaches to outperform competitors, and transform the competitive environment. Adopting new technology is frequently a required strategy for businesses to compete in the market. Firms are put under pressure when their competitors adopt new technologies (Oliveira and Martins, 2008). They prefer to adopt these technologies early in order to remain competitive. External competitive pressure will push firms to adopt AI technology to better serve their consumers and gain a competitive advantage, resulting in improved efficiency. Firms that successfully employ new AI technology to improve their products and services will gain a competitive advantage over their competitors (Hlee et al., 2023; Nam et al., 2021).

In general, a company does not have all the technical and transformational skills required to manage technologies such as AI in-house. As a result, AI adoption in businesses is typically associated with IT vendors and collaborative partners. It has been shown that vendor involvement can have a major impact on the rate of acceptance and diffusion of new goods. One of the important determinants of innovation adoption has been experimentally supported as vendor collaboration. Suppliers have a distinct and important role in the AI area. Algorithms and models, e.g., are fundamental to AI. Because many companies are not skilled at algorithms, they must create a platform available to vendors for building AI applications collaboratively. As a result, vendor collaboration can have a significant impact on the AI adoption process (Chen et al., 2021).

Human factors are critical for the adoption of AI in banking. Employee competency and training are essential factors that could promote AI adoption in the banking business. Competent employees are continually looking for innovative solutions to various business difficulties and making the best use of available chances using cutting-edge technologies. When a new technology is introduced, people who use or own it acquire power and status, whereas those who do not use it lose power and status. Some groups may have a self-interest in resisting the introduction of new technologies. These employees may either discreetly hinder the spread and use of new technologies or outright refuse to comply. As a result, it is critical to educate employees and give them with suitable training so that they may acquire the essential skills and attitudes to contribute to the set standards as well as continuous improvements in an organisation.

Another subject of discussion in relation to new technology adoption is employee acceptance of new technology. Despite its excessive cost, reports claim that people rarely use the new technology. Finally, banking customers' trust in these services and providers may be an important consideration. One of the most pressing challenges about AI adoption in banking has been identified as trust (Alizadeh et al., 2020). The most recent research on technology adoption has focused on trust as a crucial driver of technology usage patterns. Trust is defined as the consumer's willingness to accept a risk. Trust is primarily concerned with the user's perceptions of the privacy, security and quality of information and services provided by companies. Customers are sharing personal information with AI applications for their operations, which makes them sceptical of using these AI applications (AlHogail, 2018). The factors and their sub-factors are shown in Table 1.

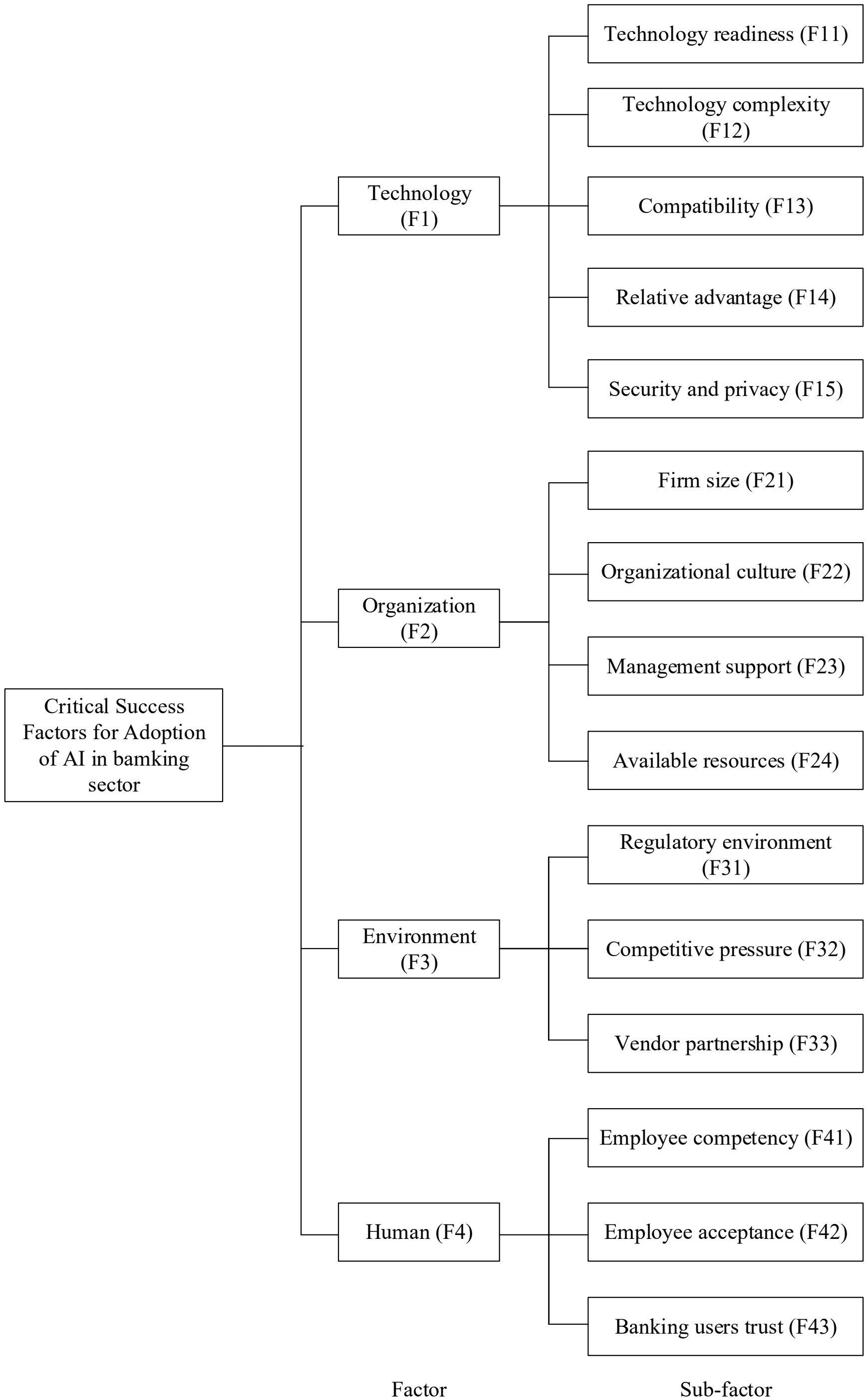
Table 1 Factors and sub-factors

Factor	*Sub-factor*	*Definition*	*Source*
	Technology readiness (F11)	A company's technology readiness refers to its ability to accept new technology. This consists of both internal (technology infrastructure) and external (market-available) technologies relevant to the company.	(Janssen et al., 2020; Richey et al., 2007)
	Technology complexity (F12)	Technology complexity is the degree to which an innovation is considered to be difficult to understand and implement.	(Oliveira et al., 2014; Rogers, 1995; Yang et al., 2013)
Technology (F1)	Compatibility (F13)	Compatibility is denoted as the fit between the desired application and technology.	(Azadegan and Teich, 2010; Chong and Bauer, 2000; Pumplun et al., 2019)
	Relative advantage (F14)	Relative advantage is the degree to which an innovation is considered to be superior to the idea it replaces.	(El Khatib et al., 2019; Ransbotham et al., 2017; Tussyadiah, 2020; Yang et al., 2013)
	Security and privacy (F15)	The most representative security and privacy attributes are confidentiality, integrity, availability, accountability and privacy-preservability.	(Spanaki et al., 2022; Xiao and Xiao, 2012)

Table 1 Factors and sub-factors (continued)

Factor	*Sub-factor*	*Definition*	*Source*
Organisation (F2)	Firm size (F21)	Firm size serves as a proxy for a variety of organizational components such as slack resources, capital, organisational structure and so on.	(Aboelmaged, 2014b; Duan et al., 2010; Hsu et al., 2006)
	Organisational culture (F22)	The organisational culture shapes staff opinions and responses to new technology and has been identified as a significant element in its acceptance and speed of adoption. Organisations with a creative culture are probably more likely to adopt AI into their business processes.	(Huang and Teo, 2020; Ward, 2013)
	Management support (F23)	Management support is critical in assigning resources for AI applications.	(Elbanna, 2013; Lo and Fu, 2016; Müller and Jugdev, 2012)
	Available resources (F24)	Resources refer to human, computer hardware, data and networking that are essential to adopt innovation.	(Ransbotham et al., 2017)
Environment (F3)	Regulatory environment (F31)	The regulatory environment refers to government policies and regulations designed to track and manage the use of new technologies.	(Agrawal et al., 2019; Chittipaka et al., 2022)
	Competitive pressure (F32)	Competitive pressure denotes the degree of perceived pressure from industry competitors.	(Baker, 2012; Oliveira and Martins, 2008; Zhu and Kraemer, 2005)
	Vendor partnership (F33)	Vendor collaboration has been experimentally supported as one of the main determinants of innovation uptake.	(Sulaiman and Wickramasinghe, 2014)
Human (F4)	Employee competency (F41)	Employee competency describes the knowledge and skills required to perform job tasks.	(Chehrehpak et al., 2018; Hernandez-de-Menendez et al., 2020)
	Employee acceptance (F42)	Employee acceptance implies employees' perspectives on how and why they welcome a certain, business-based AI application when service occurs.	(Choi, 2021; Wang et al., 2003)
	Banking users trust (F43)	Trust denotes the extent to which a user feels secured about conducting a transaction with the service provider.	(Komiak and Benbasat, 2004; Patani et al., 2014)

Figure 1 The hierarchy of factors



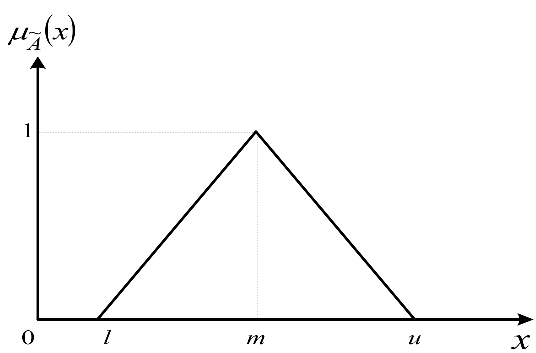
3 Methods

3.1 Fuzzy sets

Fuzzy set theory (Zadeh, 1975) was first introduced to deal with the uncertainty due to imprecision or vagueness. A fuzzy set $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X\}$ is a set of ordered pairs and X is a subset of the real numbers R, where $\mu_{\tilde{A}}(x)$ is called the membership function which assigns to each object x a grade of membership ranging from zero to one. Since its introduction, fuzzy set theory has been widely used to solve practical issues involving the analysis and processing of inaccurate information by decision-makers. A convex normalised fuzzy set has a special case known as a fuzzy number (Zimmermann, 1996). Different fuzzy numbers can be used in a variety of different situations. To cope with the ambiguity of judgments related to the performance levels of alternative alternatives with regard to each criterion, triangular and trapezoidal fuzzy numbers are commonly used. A triangular fuzzy number is created when a trapezoidal fuzzy number's two most promising values are the same (TFN). As a result, a TFN is a particular kind of trapezoidal fuzzy number. The TFN is the most popular membership function for many applications due to its simplicity and computational effectiveness. TFNs are frequently used to quantify the ambiguity of the criteria used to make decisions. TFN is represented with boundaries rather than crisp numbers to depict the fuzziness that surrounds the decision-makers when they do a pairwise comparison matrix. A triangular fuzzy number, denoted as $\tilde{A} = (l, m, u)$, has the following membership function:

$$\mu_{\tilde{A}}(x) = \begin{cases} (x - l)/(m - l); & l \le x \le m \\ (u - x)/(u - m); & m \le x \le u \\ 0; & \text{otherwise} \end{cases} \tag{1}$$

Figure 2 A triangular fuzzy number, $\tilde{A} = (l, m, u)$



A triangular fuzzy number $\tilde{A}$ is shown in Figure 2. The parameter $'m'$ is the most promising value. The parameters $'l'$ and $'u'$, respectively, are the smallest possible value and the largest possible value; they limit the field of possible evaluation. When

$l = m = u$, the triangular fuzzy number becomes a non-fuzzy number. The triplet (l, m, u) can be used to describe a fuzzy event.

Consider two TFNs $\tilde{A}_1$ and $\tilde{A}_2$, $\tilde{A}_1 = (l_1, m_1, u_1)$ and $\tilde{A}_2 = (l_2, m_2, u_2)$. The main operational laws (Gupta and Kaufmann, 1985) for two triangular fuzzy numbers $\tilde{A}_1$ and $\tilde{A}_2$ are as follows:

Addition of the fuzzy number

$$\tilde{A}_1 \oplus \tilde{A}_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \tag{2}$$

Multiplication of the fuzzy number

$$\tilde{A}_1 \otimes \tilde{A}_2 = (l_1.l_2, m_1.m_2, u_1.u_2) \text{ for } l_i > 0, m_i > 0, u_i > 0, i = 1, 2 \tag{3}$$

Division of the fuzzy number

$$\tilde{A}_1 / \tilde{A}_2 = (l_1 / u_2, m_1 / m_2, u_1 / l_2) \text{ for } l_i > 0, m_i > 0, u_i > 0, i = 1, 2 \tag{4}$$

Reciprocal of the fuzzy number

$$\tilde{A}_1^{-1} \approx \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right) \text{ for } l_1 > 0, m_1 > 0, u_1 > 0 \tag{5}$$

3.2 Fuzzy AHP

The fuzzy AHP methodology is being proposed primarily because to its ability to handle both tangible and intangible criteria. Second, it has previously been used and proven in a number of complicated real-world applications. Thirdly, it simplifies complicated problems into an uncomplicated hierarchical framework, demonstrating the decision makers' transparency. Fourth, the approach and the hierarchical structure are easily comprehensible at the operational levels because of their simplicity. Fifth, it helps the group decision makers understand the complex relationships between the problem's component parts. Lastly, it can handle imprecision from unquantifiable information, incomplete information, unobtainable information and partial ignorance because of its incorporation of fuzzy theories. The fuzzy AHP method is composed by the four aspects: (1) representation of the relative importance for pairwise comparison, (2) aggregation of fuzzy sets for group decisions and weights, (3) defuzzification of a fuzzy set to a crisp value for final comparison and (4) consistency measurement of the judgements (Liu et al., 2020). The detailed description of the fuzzy AHP method is as follows.

A matrix $\tilde{A}$ is constructed according to fuzzy pairwise comparisons.

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \vdots & \tilde{a}_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} \tag{6}$$

where $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is the fuzzy comparison value of criterion *i* to criterion *j*

The fuzzy weights of each criterion are calculated as

$$\tilde{r}_i = \left(\tilde{a}_{i1} \otimes \tilde{a}_{i2} \otimes \ldots \otimes \tilde{a}_{in}\right)^{1/n} \quad \text{for } i = 1, 2, \ldots, n \tag{7}$$

$$\tilde{w}_i = \frac{\tilde{r}_i}{\tilde{r}_1 \oplus \tilde{r}_2 \ldots \oplus \tilde{r}_n} \quad \text{for } i = 1, 2, \ldots, n \tag{8}$$

where $\tilde{r}_i$ is the geometric mean of fuzzy comparison value of criterion *i* to each criterion, and $\tilde{w}_i$ is the fuzzy weight of the *i*-th criterion.

The fuzzy weight vector $\tilde{W}$ is constructed as:

$$\tilde{W} = \left(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\right)^T \tag{9}$$

The proposed framework based on fuzzy AHP method for ranking the CSFs influencing AI adoption in banking sector is composed of the following steps:

- *Step 1 (Developing a hierarchical structure)*: The structure of the hierarchical structure is based on the identified factors and sub-factors. The system's first level is the goal, and subsequent levels are made up of factors and sub-factors. Additionally, the problem is divided into components in this stage based on their common characteristics. According to Miller (1956), most decision-makers are unable to handle more than seven to nine elements at once while making a choice.
- *Step 2 (Establishing a group of decision-makers)*: A committee of decision-makers is established. The members of the group are experts who have experience with the research issue. The relative weights of each factor and sub-factor must be determined by the decision-makers.
- *Step 3 (Determining the linguistic variables and fuzzy conversion scale)*: The importance or preference of each pair of factors is compared pairwise by the decision-makers. With the use of questionnaires and in the form of linguistic variables, it is possible to compare one factor to another. A linguistic variable is one whose values are words or sentences in a language, whether it be natural or artificial (Zadeh, 1975). The terms 'equally important', 'weakly important', 'fairly important', 'strongly important' and 'absolutely important' are used in this research to describe subjective pairwise comparisons of decision-makers. Such language values are converted into fuzzy scales using the triangular fuzzy conversion scales and linguistic scales suggested by Kahraman et al. (2006), as shown in Figure 3 and Table 2.

Figure 3 Linguistic scale for relative importance

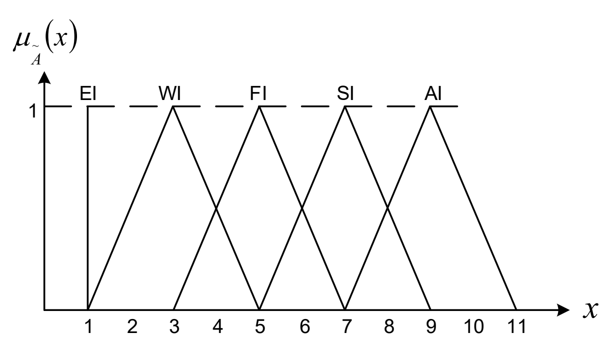


Table 2 Linguistic scales and fuzzy scales for importance

Linguistic scale for importance	*Triangular fuzzy scale*	*Triangular fuzzy reciprocal scale*
Equally important (EI)	(1, 1, 1)	(1, 1, 1)
Weakly important (WI)	(1, 3, 5)	(1/5, 1/3, 1)
Fairly important (FI)	(3, 5, 7)	(1/7, 1/5, 1/3)
Strongly important (SI)	(5, 7, 9)	(1/9, 1/7, 1/5)
Absolutely important (AI)	(7, 9, 11)	(1/11,1/9, 1/7)

- *Step 4 (Establishing comparison matrices)*: Assume there is a single-level problem with n factors, where the relative weights of factors i and j are shown as triangular fuzzy numbers $\tilde{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$. For instance, if one decision-maker believes that factor i is significantly more important than factor j, he or she may decide to set $a_{ij} = \left(1,3,5\right)$. If factor j is believed to be strongly more important than factor i, $a_{ij} = \left(1/5, 1/3, 1\right)$. Might display the pairwise comparison between the two factors. As in the traditional AHP, the comparison matrix $\tilde{A} = \left\{\tilde{a}_{ij}\right\}$ can be derived, such that

$$\tilde{A} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \cdots & 1 \end{bmatrix} \tag{10}$$

- *Step 5 (Calculating the consistency index and consistency ratio of comparison matrix)*: The consistency of an evaluation needs to be examined to guarantee a certain level of decision quality. A consistency index was proposed by Saaty (1980) as a method for measuring consistency. The pairwise comparison matrices' consistency may be determined using this index. The fuzzy comparison matrices must be transformed into crisp matrices to examine the consistency (Huang et al., 2008). There are several defuzzification methods (Huang et al., 2008; Saaty, 1980) are for obtaining a crisp number from the triangular fuzzy number (Chen and Lee, 2011). In this study, we choose to defuzzify the fuzzy numbers using the approach (Lee and Li, 1988) suggested. This approach effectively illustrates fuzziness of perception. Decision-makers can realise the uncertainties they face in various situations thanks to the representation of their preferences (α) and risk tolerance (λ). The following steps can be used to defuzzify the triangular fuzzy number $\tilde{a}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ and yield a crisp number.

$$\left(a_{ij}^{\alpha}\right)^{\lambda} = \left[\lambda . l_{ij}^{\alpha} + \left(1-\lambda\right). u_{ij}^{\alpha}\right], \quad 0 \le \lambda \le 1, 0 \le \alpha \le 1 \tag{11}$$

where $l_{ij}^{\alpha} = \left(m_{ij} - l_{ij}\right).\alpha + l_{ij}$, denotes the left-end value of α-cut for a_{ij}, $u_{ij}^{\alpha} = u_{ij} - \left(u_{ij} - m_{ij}\right).\alpha$ represents a_{ij}'s right-end value for the α-cut operation. Notably, α is any integer between 0 and 1 and may be seen as an either a steady or fluctuating situation. Through increasing α, the environment for making decisions becomes more stable. When $\alpha = 0$, there is the most uncertainty. Moreover, the range of, which measures the optimism of a decision-maker, is from 0 to 1. The decision-maker is more optimistic when λ is 0. In contrast, the decision-maker is pessimistic when λ is 1. The comparison matrix is now described as follows. In the comparison matrix, all the triangular fuzzy numbers in each element have been converted to crisp numbers:

$$\left\lfloor \left(A^{\alpha}\right)^{\lambda} \right\rfloor = \left\lfloor \left(a_{ij}\right)^{\lambda} \right\rfloor = \begin{bmatrix} 1 & \left(a_{12}^{\alpha}\right)^{\lambda} & \cdots & \left(a_{1n}^{\alpha}\right)^{\lambda} \\ \left(a_{21}^{\alpha}\right)^{\lambda} & 1 & \cdots & \left(a_{2n}^{\alpha}\right)^{\lambda} \\ \vdots & \vdots & \vdots & \vdots \\ \left(a_{n1}^{\alpha}\right)^{\lambda} & \left(a_{n2}^{\alpha}\right)^{\lambda} & \cdots & 1 \end{bmatrix} \tag{12}$$

Using the following equation, the consistence index, or CI, for a comparison matrix may be calculated.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{13}$$

where $\lambda_{\max}$ is the largest eigenvalue of the comparison matrix, and *n* is the dimension of the matrix.

According to Davies (1994), the consistency ratio is the ratio of a particular evaluation matrix's consistency to the consistency of a random matrix.

$$CR = \frac{CI}{RI(n)} \tag{14}$$

where $RI(n)$ is a random index that depends on *n*, as shown in Table 3.

Table 3 Random index (RI) of random matrices

n	*3*	*4*	*5*	*6*	*7*	*8*	*9*
RI(n)	0.58	0.9	1.12	1.24	1.32	1.41	1.45

An admissible comparison matrix has a Consistency Ratio (CR) of equal to or less than 0.1. The decision-maker is advised to conduct additional pairwise comparisons if the CR is unacceptable.

- *Step 6 (Constructing the representative matrix of all decision-makers)*: Aggregation is required to get a decision-maker group consensus since each individual judgment matrix reflects the viewpoint of a single decision-maker. Aggregation of individual judgements (AIJ) and aggregation of individual priorities (AIP) are the two fundamental methods used in the traditional AHP to combine individual preferences into a group preference (Forman and Peniwati, 1998). The FAHP can also make use of the concepts and ideas used in the traditional AHP. The group judgment matrix is derived from the individual judgment matrices using the AIJ approach. This implies that the priorities of a 'new individual' are determined as a group solution, and the group judgment matrix is regarded as the judgment matrix of this 'new individual.' The AIP approach, however, has each group member operate on their own. Particularly, we get the individual priorities from the individual judgment matrices, and the group priorities are then obtained from these. The complexity of the necessary fuzzy arithmetic operations determines whether to utilise AIJ or AIP. In this study, we aggregate group decisions using the AIJ technique.

Suppose that there exists a group of K decision-makers participating in the study. They make pairwise comparison of n criteria. As a result of the pairwise comparisons, we get a set of K matrices $\tilde{A}_k = \left\{\tilde{a}_{ijk}\right\}$, where $\tilde{a}_{ijk} = \left(l_{ijk}, m_{ijk}, u_{ijk}\right)$. denotes a relative importance of criterion i to j, as assessed by the expert k. . The following equation may be used to determine the triangular fuzzy numbers in the group judgment matrix (Büyüközkan and Feyzioğlu, 2004):

$$l_{ij} = \min_{k=1,2,\ldots,K}\left(l_{ijk}\right)$$

$$m_{ij} = \sqrt[K]{\prod_{k=1}^{K} m_{ijk}} \tag{15}$$

$$u_{ij} = \max_{k=1,2,\ldots,K}\left(u_{ijk}\right)$$

- *Step 7 (Calculating the weights of criteria and sub-criteria)*: The weights of the criterion and sub-criteria are then determined using the extended analysis FAHP approach.

3.3 Data collection

To collect data, a team of twenty key domain experts was formed for the decision-making panel, which includes four Chief Information Officers (CIOs), four database administrators, three IT Managers, three help desk technicians, three computer support specialists, and three cyber security analysts who work in the banking sector in Vietnam and have more than ten years of expertise in the field. The finalised list of 15 factors of AI adoption in banking has been grouped into four key groups based on the research framework after several phases of discussion with experts. These are technological, organisational, environmental and human measurement. Finally, the factors and sub-factors are completely depicted and introduced in Table 1.

The questionnaire instrument was designed using the primary attributes of the FAHP method's factor comparison and a scale of 1–5 for each comparison between factors. In August 2023, the questionnaire was distributed to experts who were involved in the previous step of factor investigation and had roles and responsibilities that might provide a holistic view of the technology, organisation, environment and human factors during the study. After the experts' comparison matrices of factors and sub-factors are formed, then the Consistency Ratios (CRs) are calculated. Four questionnaires had inappropriate answers among the returned responses. As a result, their feedback was removed from the analysis. Sixteen (16) respondents have CR values that are all less than 0.1. As a result, the outcomes of this study are based on the viewpoints of 16 experts.

4 Results and discussions

The FAHP method is used to determine the ranking of the influence of factors and sub-factors on the successful implementation of AI in banking sector. The calculation is done according to the hierarchy that has been formed in the theoretical framework which consists of technology, organisation, environment and human criteria. After the questionnaire results are received and accepted, a geometric mean calculation is performed to form a consensus pairwise comparison matrix for each technology, organisation, environment and human factor and sub-factor; then the consistency ratio of each pairwise comparison matrix is calculated; then calculate the weight of each factor and sub-factor to determine the local ranking and global ranking. To calculate the global weight of sub-factors and global rank, multiply the weight of each factor by the weight of the sub-factor. The results of consensus pairwise comparison matrices, global weights and ranks are found in Tables 4 to 14. Figure 4 shows the rank of sub-factors influencing AI adoption in banking sector.

Table 4 Aggregate comparison matrix of factor

	F1	*F2*	*F3*	*F4*
F1	(1, 1, 1)	(1, 3, 5)	(0.2, 0.33, 1)	(0.2, 0.33, 1)
F2	(0.2, 0.33, 1)	(1, 1, 1)	(1, 1, 1)	(0.14, 0.26, 1)
F3	(1, 3, 5)	(1, 1, 1)	(1, 1, 1)	(0.14, 0.23, 1)
F4	(1, 3, 5)	(1, 3.87, 7)	(1, 4. 4, 7)	(1, 1, 1)

Table 5 Fuzzy weights of factor

Criteria	*Fuzzy weights*
F1	(0.056, 0.156, 0.605)
F2	(0.052, 0.111, 0.404)
F3	(0.077, 0.186, 0.605)
F4	(0.126, 0.547, 1.6)

Table 6 Aggregate comparison matrix of sub-factor within Technology (F1)

	F11	*F12*	*F13*	*F14*	*F15*
F11	(1, 1, 1)	(1, 1.35, 7)	(1, 1, 1)	(1, 4.54, 7)	(0.11, 0.15, 0.33)
F12	(0.14, 0.74, 1)	(1, 1, 1)	(1, 1.41, 5)	(0.2, 1.99, 5)	(0.14, 0.2, 0.33)
F13	(1, 1, 1)	(0.2, 0.71, 1)	(1,1,1)	(1, 1, 1)	(0.11, 0.14, 0.2)
F14	(0.14, 0.22,1)	(0.2, 0.5, 5)	(1, 1, 1)	(1, 1, 1)	(0.11, 0.18, 0.33)
F15	(3, 6.57, 9)	(3, 5, 7)	(5, 7, 9)	(3, 5.55, 9)	(1, 1, 1)

Table 7 Fuzzy weights of sub-factor within Technology (F1)

Sub-factor	*Fuzzy weights*
F11	(0.061, 0.139, 0.395)
F12	(0.031, 0.118, 0.345)
F13	(0.044, 0.089, 0.164)
F14	(0.03, 0.064, 0.25)
F15	(0.251, 0.589, 1.246)

Table 8 Aggregate comparison matrix of sub-factor within Organisation (F2)

	F21	*F22*	*F23*	*F24*
F21	(1, 1, 1)	(0.14, 0.2, 0.33)	(0.11, 0.14, 0.2)	(0.11, 0.14, 0.2)
F22	(3, 5, 7)	(1, 1, 1)	(0.2, 0.62, 1)	(0.2, 0.62, 1)
F23	(5, 7, 9)	(1, 1.62, 5)	(1, 1, 1)	(0.2, 0.71, 5)
F24	(5, 7, 9)	(1, 1.62, 5)	(0.2, 1.41, 5)	(1, 1, 1)

Table 9 Fuzzy weights of sub-factor within Organisation (F2)

Sub-factor	*Fuzzy weights*
F21	(0.021, 0.049, 0.122)
F22	(0.061, 0.23, 0.582)
F23	(0.103, 0.329, 1.386)
F24	(0.103, 0.391, 1.386)

Table 10 Aggregate comparison matrix of sub-factor within Environment (F3)

	F31	*F32*	*F33*
F31	(1, 1, 1)	(1, 4.26, 7)	(1, 3, 5)
F32	(0.14, 0.23, 1)	(1, 1, 1)	(0.2, 0.33, 1)
F33	(0.2, 0.33, 1)	(1, 3, 5)	(1, 1, 1)

Table 11 Fuzzy weights of sub-factor within Environment (F3)

Sub-factor	*Fuzzy weights*
F31	(0.167, 0.621, 1.73)
F32	(0.051, 0.114, 0.529)
F33	(0.098, 0.266, 0.905)

Table 12 Aggregate comparison matrix of sub-factor within Human (F4)

	F41	*F42*	*F43*
F41	(1, 1, 1)	(1, 1, 1)	(0.11, 0.17, 0.33)
F42	(1, 1, 1)	(1, 1, 1)	(0.11, 0.15, 0.33)
F43	(3, 6.04, 9)	(3, 6.57, 9)	(1, 1, 1)

Table 13 Fuzzy weights of sub-factor within Human (F4)

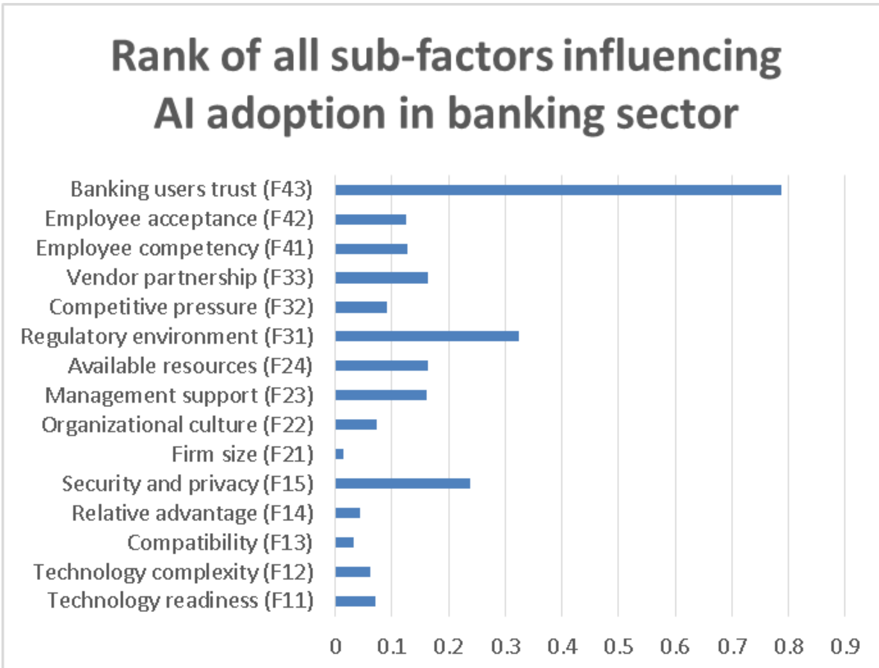
Sub-factor	*Fuzzy weights*
F41	(0.084, 0.122, 0.228)
F42	(0.084, 0.119, 0.228)
F43	(0.364, 0.759, 1.423)

Table 14 Global weight and rank of factors and sub-factors

Factor	*Factor weight*	*Sub-factor weight in relation to the factor weight*	*Global weight*	*Global weight (crisp value)*	*Rank*
Technology (F1)	*(0.056, 0.156, 0.605)*			*0.243*	*3*
Technology readiness (F11)		(0.061, 0.139, 0.395)	(0.003, 0.022, 0.239)	0.071	11
Technology complexity (F12)		(0.031, 0.118, 0.345)	(0.002, 0.018, 0.209)	0.062	12
Compatibility (F13)		(0.044, 0.089, 0.164)	(0.002, 0.014, 0.099)	0.032	14
Relative advantage (F14)		(0.03,0.064,0.25)	(0.002, 0.01, 0.151)	0.043	13
Security and privacy (F15)		(0.251, 0.589, 1.246)	(0.014, 0.092, 0.754)	0.238	3
Organisation (F2)	*(0.052, 0.111, 0.404)*			*0.170*	*4*
Firm size (F21)		(0.021, 0.049, 0.122)	(0.001, 0.005, 0.049)	0.015	15
Organisational culture (F22)		(0.061, 0.23, 0.582)	(0.003, 0.026, 0.235)	0.072	10
Management support (F23)		(0.103, 0.329, 1.386)	(0.005, 0.037, 0.56)	0.160	6
Available resources (F24)		(0.103, 0.391, 1.386)	(0.005, 0.043, 0.56)	0.163	5
Environment (F3)	*(0.077, 0.186, 0.605)*			*0.264*	*2*
Regulatory environment (F31)		(0.167, 0.621, 1.73)	(0.013, 0.115, 1.047)	0.323	2
Competitive pressure (F32)		(0.051, 0.114, 0.529)	(0.004, 0.021, 0.32)	0.092	9
Vendor partnership (F33)		(0.098, 0.266, 0.905)	(0.008, 0.049, 0.547)	0.163	4
Human (F4)	*(0.126, 0.547, 1.6)*			*0.705*	*1*
Employee competency (F41)		(0.084, 0.122, 0.228)	(0.011, 0.067, 0.365)	0.127	7
Employee acceptance (F42)		(0.084, 0.119, 0.228)	(0.011, 0.065, 0.365)	0.126	8
Banking users trust (F43)		(0.364, 0.759, 1.423)	(0.046, 0.415, 2.276)	0.788	1

As shown in Table 14, Human (F4) is the highest ranked critical success factor, followed by Environment (F3) in second place, Technology (F1) in third place and Organisation (F2) in fourth place.

Figure 4 Rank of sub-factors influencing AI adoption in banking sector



As shown in Table 14 and Figure 4, banking users trust sub-factor became the greatest weight (0.788) in AI adoption. This finding is in line with that of previous studies (AlHogail, 2018; Belanche et al., 2012; Tams et al., 2018; Yildirim and Ali-Eldin, 2019) which indicated a strong effect of users' trust in comparison to other factors in technology adoption. Users are concerned that their sensitive information will fall into the wrong hands or be misused. It is linked to security since ensuring system security and user safety is critical to building trust. It was discovered that customer trust influenced their decision to use an advanced technology (AI adoption). Customers are more likely to use the technology if they have trust in it. This orientation is based on the exchange of information and services with a trusted partner (Rotchanakitumnuai and Speece, 2003).

Regulatory environment (F31) stands second in the critical success factors of AI adoption in banking. Risk awareness, regulatory requirements and intervention in the banking service environment have increased in the aftermath of the global financial crisis. Government regulations have played an essential part in driving AI adoption. Similarly, the current study's findings regarding AI adoption indicate the same. Conventional data protection is a core business of the banking sector. The development of FinTechs forced traditional financial service providers to change. Regulatory limitations, among other things, have limited the financial and personal resources of the banking sector, while governmental regulations establish opportunities for new market participants and AI adoption is hampered by ethical concerns (Kruse et al., 2019).

Security and privacy (F15) hold the third position among the vital success factors of AI adoption in the banking industry. This AI application in banking efficiently assists the organisation in data analysis. Organisations relies mostly on an AI-integrated system that meets their business requirements. However, working with data involves a number of challenges, including security and privacy concerns. Customers must be certain that their personal information will not be abused (Kruger et al., 2010). They must be satisfied that their data's security and privacy are protected. They will then openly share their information with the other groups. As a result, organisational authorities must take client data security and privacy very seriously and honestly. Customers will build trust as a result of this (Chatterjee et al., 2021a).

Nevertheless, firm size (F21) and compatibility (F13) were the least influential factors. Several academics in the field of innovation have analysed firm size factor, which is regarded as a leading indication of organisational complexity. However, several other research, including this one, found little connection between firm size and technology adoption (e.g., cloud computing (Alhammadi et al., 2015). Meanwhile, compatibility, according to the Diffusion of Innovation Theory, is a critical technology attribute recognised by consumers. The decision to choose a new system is driven by compatibility. Gangwar et al. (2015); Guo and Liang (2016) and Salah et al. (2021) carried out to provide a description of the compatibility role and its influence on IT innovation adoption. The degree to which an invention is perceived as being consistent with the current values, historical experience and needs of potential adopters is referred to as compatibility. It can be inferred from the finding that AI applications are popular in the Vietnamese context, and individuals and organisations are familiar with their application in a variety of disciplines. As a result, compatibility plays little role in the adoption of AI technologies in the banking sector.

5 Managerial implications

In two ways, this study contributes to research and practice. First, it provides a literature study to investigate factors driving AI adoption in the banking sector in Vietnam. Second, it ranks the influential factors of AI adoption. Researchers may use this work to further analyse AI adoption concerns and produce a reliable literature in the field of banking. Furthermore, AI developers might utilise this study as a guide to the most influential aspects that could improve their decision to adopt AI products, producing value for both users and providers.

The study offers a literature review to explore the CSFs influencing AI adoption. The proposed theoretical model is for AI, an innovative technology in banking. The suggested factors and sub-factors are based on existing literature. This work responds to the call for additional research and empirical studies on intelligent automation in the banking sector by providing a conceptual model for AI adoption, as there is currently a scarcity of studies that investigate the change in the ways banking organisations are performed due to the emerging technologies such as AI and robotics. Scholars can utilise the findings to investigate various new advanced technology adoption practices in banking. This finding may be used by researchers to further investigate factors influencing AI adoption in banking sector and create a trustworthy literature in the other sectors.

The development of an adequate framework for identifying and assessing critical factors affecting the adoption of artificial intelligence in the banking industry is the study's primary strength. In order to rank the most important success factors for the implementation of artificial intelligence in financial organisations, this paper suggests using the FAHP technique. A comprehensive literature research and expert panel judgment have precisely determined 15 critical success factors. The relative importance of each of these factors and how they affect the adoption of AI have been determined using FAHP. The findings show that, out of all the elements, the 'banking users trust' component is the most important. Thus, by arranging success factors in order of importance, practitioners can determine which factors require their attention first. As a result, in times of scarcity, this relative importance can be highly helpful to the organisations when establishing improvement programs.

By identifying the factors influencing AI adoption in banking, this study delivers important insights for practitioners and managers. This study provides some of the managerial viewpoints that can be used to understand the adoption of AI in the banking sector. By considering the rank of factors found, organisations can better assess their ability to adopt AI successfully and know which changes to make. According to the findings, the most crucial factor in AI adoption is banking user trust. Marketers and designers of AI applications in banking need to ensure that bank users' trust issues should be extensively investigated. To increase consumer trust in AI applications and grow the market, the product should appear useful to consumers with clear benefits, capabilities and features that focus on the customer experience. Furthermore, in order to gain user trust in AI technology, it must be reliable and trustworthy, meet standards and meet some user expectations and standards. Overall, product functionality and durability, particularly in hostile environments, are critical to ensuring consumer trust in AI goods and services. In addition, AI application operators must persuade users that they have a high level of trust.

In addition to users' trust, regulatory environment has been recognised as one of the factors that firms need to consider. The regulatory environment's goals have been to design a policy framework that would encourage and support disruptive innovation to improve financial inclusion and economic growth while also protecting the safety and soundness of the banking system and overall financial stability. In designing regulations, regulators should seek to provide clear rules, maintain market integrity and encourage advanced technology adoption.

6 Conclusions

A number of factors that affect the banking industry's adoption of artificial intelligence have been evaluated in this study. In order to rank the crucial success elements of AI adoption related to banking organisations, the paper proposes employing the FAHP methodology. A literature review and the opinions of an expert panel have resulted in the identification of a total of 15 critical factors. The relative importance of each of these characteristics and how they affect the various experience dimensions have been determined through the use of FAHP. The results show that, out of all the factors, the 'banking users trust' element is the most important. The findings provide direction for practitioners in increasing the likelihood of successful adoption of AI. Future research can be done in several directions. In this study, a group of experts discussed the factors affecting AI adoption in banking. However, there may be some differences in cultural beliefs or political regulations between groups of people. Therefore, further studies should be conducted in different communities to validate the validity of the proposed model given in this study. Furthermore, FAHP makes the assumption that all of the different decision-making factors and sub-factors are independent of one another, but while dealing with the real-world problems, it is not always possible for the banking organisations to consider this assumption. This may be considered an additional limitation. This is left to future researchers to nurture.

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