DETERMINANTS INFLUENCING THE ADOPTION OF ARTIFICIAL INTELLIGENCE TECHNOLOGY IN NON-LIFE INSURERS

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Abstract

Although artificial intelligence (AI) technology has been widely used in the insurance industry at a global scale, studies examining the adoption of AI technology in emerging markets are few and far between. This paper fills this gap by using Cronbach's alpha, exploratory factor analysis, confirmatory factor analysis, and structural equation model (SEM) to discover significant factors affecting their behavioral intentions to adopt AI technology in Vietnam, a developing country. Data is collected from nearly 470 employees in Vietnamese non-life insurance firms. Empirical findings show that the most important determinant influencing the adoption of AI technology in Vietnamese non-life insurers is attitudes toward adoption. Attitudes toward adoption are positively related to the perceived ease of use and perceived usefulness, consistent with Gupta et al. (2022). Although perceived risk has a negative influence on the behavioral intention to adopt AI technology, it is not a serious issue for insurance companies.

Keywords: Artificial Intelligence, Emerging Market, Non-Life Insurance, Organizational Behavior, Technology Acceptance Model

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1. INTRODUCTION

Artificial intelligence (AI), originally developed in the 1950s, is known as a computer system whose intelligence is equal to that of a human (Eling et al., 2022). Since AI has the power to enhance and improve organizational performance by solving complex business challenges, it is adopted in various industries, such as manufacturing, education, food service, construction, tourism, transportation, finance and insurance, etc. More and more enterprises are using AI applications in all operating activities, making AI a leading strategic technology (Phuoc, 2022).

Recently, adopting AI technology has become a popular trend in the insurance industry all over the world. According to Ceylan (2022), the vast majority of insurers currently have several activities in relation to AI technology, with 30% actively looking at opportunities, and another 50% fully consistently investing in new AI technology. Thanks to the ability to perform complex computational tasks, AI technology is rapidly transforming various financial services industries, particularly within non-life insurance. AI has a broad effect along the entire value chain of insurance from product design to underwriting and actuarial activities and claims management (Xu & Zweifel, 2020). Adopting AI technology leads to both pros and cons for insurance firms. On the one hand, AI-enabled applications could be used to deal with numerous policy enrollments and claim settlements, build new products, enhance customer experience, etc. On the other hand, several potential risks also arise, such as cyber-attacks and identity theft.

Although factors affecting AI adoption in many countries are intensively investigated (Horowitz & Kahn, 2021; Grover et al., 2022; Chen et al., 2022; Sudaryanto et al., 2023; Na et al., 2023), the studies for Vietnam are still sparse. This paper contributes to the literature review on AI adoption in Vietnam, the second fastest-growing economy in Southeast Asia. After two decades of development, the Vietnamese non-life insurance market thrived dramatically with a growth rate in revenue of nearly 15% per year. At the end of 2022, the revenue of non-life insurance reached approximately $3.7 billion, accounting for 1% of the national gross domestic product (GDP). Due to the current mainstream of digital transformation in Vietnam, both state agencies and insurance firms expect that AI technology will boom in the following years. However, according to Pham et al. (2022), less than 10% of Vietnamese companies are actively developing their AI applications. Many insurance employees are unwilling to use AI technology due to potential risks, ease of use, facilitating conditions, etc. Hence, we aim to provide an adequate understanding of AI adoption in non-life insurers and its key drivers in Vietnam. This research conducts a survey among employees in Vietnamese non-life insurance firms, who directly use AI technology for their work.

Based on data from nearly 470 questionnaires, we find that the behavioral intention to adopt AI technology is negatively impacted by perceived risk. Its coefficient is only approximately -0.2, indicating that insurance employees do not pay a large amount of attention to perceived risk. The strongest determinant of AI adoption in Vietnamese non-life is attitudes toward adoption, which is positively related to perceived usefulness and perceived ease of use. Finally, facilitating conditions and perceived self-efficacy of employees also play essential roles in adopting AI technology in Vietnamese non-life insurers.

The rest of this article is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology. Section 4 presents and discusses the empirical results, then Section 5 draws the conclusions.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

With the wide application of AI technology in various industries, there are several papers analyzing factors affecting the adoption of AI. Examining questionnaires of 690 United States officials, Horowitz and Kahn (2021) point out that the behavioral intention to adopt AI technology is negatively affected by perceived risk, especially the theft of personal information through cyber-attacks. Adoption of AI in an organization depends on the computing infrastructure and training of employees, known as facilitating conditions (Grover et al., 2022). According to Islam et al. (2022), the availability of technical and organizational infrastructures, considered facilitating conditions, significantly promotes the behavioral intention to adopt AI technology. Furthermore, the behavioral intention to adopt AI is regarded as a sustainable predictor of actual adoption. Li et al. (2022) state that the behavioral intention to use AI of medical students is predicted by their perceived usefulness and perceived self-efficacy. According to Chen et al. (2022), perceived ease of use and perceived usefulness are the two most significant determinants influencing AI adoption in business-to-business marketing. While these two factors also significantly affect the AI adoption of accounting students in Indonesia (Sudaryanto et al., 2023), technology readiness and digital competence play no role. Na et al. (2023) document that satisfaction with AI technology is linked to the perceived ease of use and perceived usefulness, leading to higher intention to adopt AI technology in Korean construction firms. In the insurance industry, Gupta et al. (2022) state that managerial capability and usefulness significantly predict behavioral intention of adopting AI in India.

The impact of AI on the insurance industry in developed markets is also comprehensively investigated. According to Eling et al. (2022), AI adoption not only creates new revenue streams for insurers but also enhances cost efficiency. Computer systems with AI are able to recognize patterns in the insured's data, and then procedure a more accurate estimation of loss likelihood. As a result, insurance firms can automate the underwriting processes and manage claim settlements more effectively. Furthermore, thanks to individual information collected by AI, insurance products are tailored to each customer and their current situation, enhancing their experience (Zarifis & Cheng, 2022). The application of AI in insurance also creates several potential risks. To recognize patterns, computer systems should be trained with a large amount of data, which could be a vulnerable target for cyber-attacks. More dangerously, the insured's data includes individual information such as bank accounts, national identity, social security numbers, etc. Furthermore, insufficient data leads to biased estimation of loss probabilities. Then, the underwriting processes might be erroneous.

To the best of our knowledge, in-depth research on the adoption of AI technology in Vietnam is still limited. Phuoc (2022) examines AI adoption by surveying nearly 200 managers in Vietnamese firms. Empirical results show that the technical complexity (or perceived ease of use), top management support, and usefulness are critical factors affecting the adoption of AI in Vietnam. Pham et al. (2022) investigate the intention to use insurance applications of Vietnamese customers. Based on 166 questionnaires, they find that usefulness, ease of use, and trust have a positive impact on the intention to use insurance applications. Meanwhile, perceived risk seems to be an insignificant factor. Since there is no published paper analyzing the adoption of AI technology in the Vietnamese insurance industry, we contribute to the literature review on AI adoption in Vietnam. Hypotheses are built as follows.

Perceived risk (*PR*): Various papers indicate that users' perceived risk has an important impact on the adoption of AI technology (Cukurova et al., 2020; Horowitz & Kahn, 2021). According to Horowitz and Kahn (2021), perceived risk negatively influences AI adoption.

H1: Perceived risk negatively influences the behavioral intention to adopt artificial intelligence technology in Vietnamese non-life insurance companies.

Perceived self-efficacy (*PSE*)*:* According to Kulviwat et al. (2014), self-efficacy plays an essential role in shaping the impact of cognition and its effects on high technology adoption. Li et al. (2022) prove that perceived self-efficacy positively supports the perceived usefulness of AI technology applications.

H2: Perceived self-efficacy of employees in insurance firms positively influences the perceived usefulness of artificial intelligence technology in Vietnamese non-life insurance companies.

Facilitating condition (*FC*): Alam et al. (2020) define facilitating condition as the availability of necessary infrastructure and organization to adopt the AI-powered system. For example, user-friendly computing infrastructure and guidelines to use AI-based software fuel AI adoption. Grover et al. (2022) also imply that the facilitating condition is the key determinant affecting the perceived ease of use of technology users.

H3: Facilitating conditions positively influence the perceived ease of use of artificial intelligence technology in Vietnamese non-life insurance companies.

Perceived ease of use (*PEOU*): Perceived ease of use measures how well the user adopts an AI-based software without effort, known as one of the major variables of the technology acceptance model. Perceived ease of use is confirmed to influence the perceived usefulness as well as the behavioral intention to adopt AI technology in the existing literature (Chen et al., 2022; Sudaryanto et al., 2023; Na et al., 2023).

H4: Perceived ease of use positively influences the perceived usefulness of artificial intelligence technology in Vietnamese non-life insurance companies.

H5: Perceived ease of use positively influences attitudes toward adopting artificial intelligence technology in Vietnamese non-life insurance companies.

Perceived usefulness (*PU*): Perceived usefulness is the degree to which users believe that adopting AI technology would enhance their productivity. Perceived usefulness has a positive effect on the attitude to adopt AI technology, as reported in several studies (Li et al., 2022; Chen et al., 2022; Pham et al., 2022; Gupta et al., 2022).

H6: Perceived usefulness positively influences attitudes toward adopting artificial intelligence technology in Vietnamese non-life insurance companies.

Attitudes toward adoption (*AT*): According to Na et al. (2023), attitudes toward adopting AI technology refer to a physical tendency reflected by evaluating AI technology with a level of satisfaction or non-satisfaction. Attitudes toward adoption are reported to directly influence the behavioral intention to adopt AI technology (Pham et al., 2022; Na et al., 2023; Correia & Água, 2023).

H7: Attitudes toward adoption positively influence the behavioral intention to adopt artificial intelligence technology in Vietnamese non-life insurance companies.

3. RESEARCH METHODOLOGY

This study aims to examine determinants influencing the adoption of AI technology in Vietnamese non-life insurance companies. Based on the literature review, we propose a framework of factors affecting AI technology adoption. A pilot study with 15 experts is initially used to redefine determinants as well as test the validity of the questionnaire. The final questionnaire includes two parts. The first part provides demographic information of respondents. The second part consists of questions related to factors influencing the adoption of AI technology. Then, we designed a questionnaire in Google Forms and sent it to nearly 500 employees in Vietnamese non-life insurance companies from April 5 to April 25, 2023; 468 fulfilled responses meeting the preset requirements are collected. Demographics of respondents are given in Table 1. In terms of gender, the majority of respondents are male (54.5%) and their ages range between 40 and 49 years old. The highest educational attainment belongs to college/university, at nearly 75%. In terms of positions, about 84% of respondents are employees.

Table 1. Demographics of respondents

Item	***Demographics***	***Frequency***	***Percentage (%)***
Gender	Male	255	54.5
	Female	213	45.5
Age	20–29 years old	85	18.2
	30–39 years old	147	31.4
	40–49 years old	163	34.8
	From 50 years old upwards	73	15.6
Education	High school	39	9.3
	College/university	348	74.4
	Graduate school	81	17.3
Position	Director/vice director	11	2.4
	Head/vice head of department	63	13.5
	Staff	394	84.2
Total		468	100.0

Figure 1. The research framework model

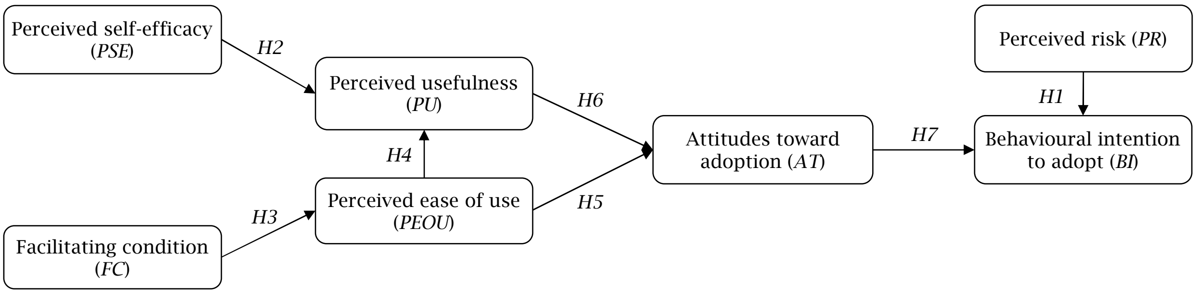
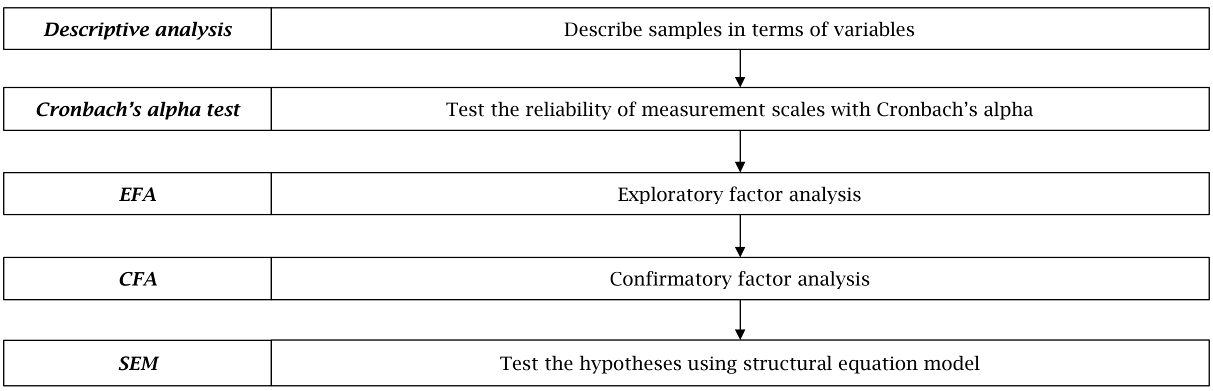


Table 2. Determinants, attributes and codings

No.	***Determinants***	***Attributes***	***Codes***
1	*Perceived risk*		*PR*
1.1		I believe that adopting AI technology is risky since it requires a large amount of investment.	*PR1*
1.2		I am concerned about data and information security when adopting AI technology.	*PR2*
1.3		For high-value and long-term contracts, adopting AI technology might lead to a higher level of risk.	*PR3*
2	*Perceived self-efficacy*		*PSE*
2.1		I feel confident when adopting AI technology.	*PSE1*
2.2		I can adopt AI technology to search and communicate with customers.	*PSE2*
2.3		I can easily adopt AI technology without any guidelines.	*PSE3*
3	*Facilitating condition*		*FC*
3.1		The company creates favorable conditions for employees to attend AI technology training.	*FC1*
3.2		I am always supported by a technical department if there is any problem in adopting AI technology.	*FC2*
3.3		I can access the guidelines for adopting AI technology at any time.	*FC3*
4	*Perceived ease of use*		*PEOU*
4.1		It is easy to understand the guidelines for adopting AI.	*PEOU1*
4.2		I believe that manipulations of adopting AI technology are simple.	*PEOU2*
4.3		I believe that I can be quickly proficient in adopting AI technology.	*PEOU3*
5	*Perceived usefulness*		*PU*
5.1		Thanks to adopting AI technology, my productivity could be improved significantly.	*PU1*
5.2		Thanks to adopting AI technology, my company could reduce operating expenses.	*PU2*
5.3		I believe that adopting AI technology contributes to the company's growth.	*PU3*
6	*Attitudes toward adopting*		*AT*
6.1		I totally agree that my company should adopt AI technology.	*AT1*
6.2		I like adopting AI technology.	*AT2*
6.3		I believe that investing in AI technology is worthy.	*AT3*
7	*Behavioral intention to adopt*		*BI*
7.1		I always expect my company to adopt AI technology.	*BI1*
7.2		I intend to adopt AI technology to collect data with the aim of analyzing the customers' demand and handling claims.	*BI2*
7.3		I always want to adopt AI technology in the near future.	*BI3*

The research process is summarized in Figure 2. The first step is descriptive analysis, which describes samples in terms of variables. Secondly, we test the reliability of measurement scales with Cronbach's alpha. The two next steps are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Finally, we test hypotheses by running the structural equation model (SEM).

Figure 2. The research process



4. RESEARCH RESULTS AND DISCUSSION

4.1. Reliability of measurement scales with Cronbach's alpha

According to Hair et al. (2019), Cronbach's alpha of measurements should be greater than 0.6 and the corrected item-total correlation of all observed variables should be higher than 0.3. Since the adjusted correlation of *PR3* is less than 0.3, it is removed. Finally, there are 20 observed variables of seven measurements as displayed in Table 4.

Table 4. Cronbach's alpha test results

Scale	*Items*	*Cronbach's alpha*
Perceived risk	*PR1, PR2*	0.873
Perceived self-efficacy	*PSE1, PSE2, PSE3*	0.931
Facilitating condition	*FC1, FC2, FC3*	0.891
Perceived ease of use	*PEOU1, PEOU2, PEOU3*	0.784
Perceived usefulness	*PU1, PU2, PU3*	0.901
Attitudes toward adoption	*AT1, AT2, AT3*	0.898
Behavioral intention to adopt	*BI1, BI2, BI3*	0.896

4.2. Exploratory factor analysis

The remaining 20 observed variables are entered for EFA as outlined in Table 5. Since *PEOU1* loads on 2 factors, it is removed. Factor loading of 19 other variables are all greater than 0.5. The Kaiser-Meyer-Olkin (KMO) coefficient is 0.811, considerably higher than 0.5. Therefore, EFA is necessary for the data analysis. Bartlett's test has a p-value of 0.00, lower than the significance level of 0.05. Thus, the observed variables are correlated with each other in the population (Denis, 2018). Finally, there are seven significant determinants, explaining about 72% of the variance of data. Random components and variables outside the model account for the remaining 28%.

Table 5. Rotated component matrix

Observed variables	*Determinants*						
	1	*2*	*3*	*4*	*5*	*6*	*7*
PSE1	0.929						
PSE3	0.899						
PSE2	0.892						
AT1		0.935					
AT3		0.839					
AT2		0.821					
FC1			0.968				
FC3			0.861				
FC2			0.752				
PU1				0.928			
PU3				0.860			
PU2				0.800			
BI1					0.960		
BI3					0.827		
BI2					0.756		
PR1						0.887	
PR2						0.874	
PEOU3							0.872
PEOU2							0.871

4.3. Confirmatory factor analysis

The CFA is used to evaluate the measurement model. Since all the goodness of fit indexes are ranged in the recommended values (see Table 6), we find a good fit. The reliability of the measurement scales is evaluated in terms of average variance extracted (AVE) and composite reliability (CR). According to Denis (2018), the criteria to test convergent validity are AVE ≥ 50% and CR ≥ 0.70. AVE is ranged from 74.6% to 77.4%, (≥ 50%) and CR is ranged from 0.870 to 0.901 (≥ 0.70), indicating that the measurement scales are valid and reliable.

Table 6. Goodness of fit (CFA and SEM)

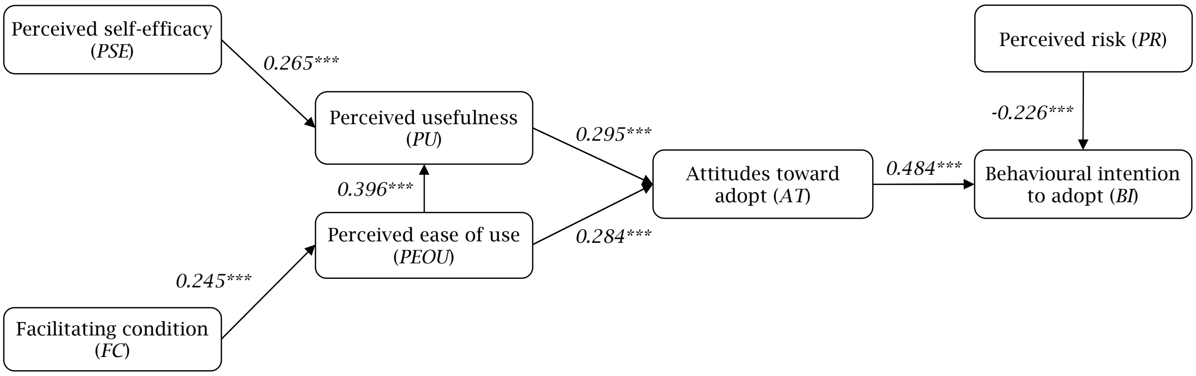
Items	*Acceptable ranges*	*CFA*	*SEM*
CMIN/DF	< 5.00	2.239	3.148
CFI	> 0.90	0.970	0.943
GFI	> 0.90	0.933	0.922
AGFI	> 0.85	0.902	0.894
RMSEA	< 0.08	0.056	0.073

Note: The CMIN/DF stands for Chi-square statistics/degree of freedom, implying discrepancy divided by degree of freedom. The GFI stands for goodness of fit index. The AGFI stands for adjusted goodness of fit index. The CFI stands for comparative fit index. The RMSEA stands for root mean square error of approximation. Acceptable ranges are collected from Hair et al. (2019).

4.4. Structural model and hypotheses testing

According to Table 6, all the fit values for the structural model are ranged in the recommended values. Therefore, the structural model achieves a good level of fit. The SEM is performed to test the hypotheses proposed in Section 2. Results are summarized in Figure 3 and Table 7.

Figure 3. Structural model results



*Note: *** Significance at 1% level.*

Table 7. Hypotheses testing results

Hypothesis	*Causal path*	*Unstandardized coefficient*	*Standardized coefficient*	*Std. error*	*CR*	*p-value*
H1	*BI* ← *PR*	-0.182	-0.226***	0.041	4.478	0.000
H2	*PEOU* ← *FC*	0.234	0.245***	0.039	6.082	0.000
H3	*PU* ← *PSE*	0.223	0.265***	0.041	5.407	0.000
H4	*PU* ← *PEOU*	0.544	0.396***	0.071	7.691	0.000
H5	*AT* ← *PEOU*	0.387	0.284***	0.074	5.196	0.000
H6	*AT* ← *PU*	0.291	0.295***	0.055	5.304	0.000
H7	*BI* ← *AT*	0.415	0.484***	0.043	9.692	0.000
Structural equations:						
PEOU = 0.345 *FC* *PU* = 0.265 *PSE* + 0.396 *PEOU* *AT* = 0.284 *PEOU* + 0.295 *PU* *BI* = 0.484 *AT* – 0.226 *PR*						

*Note: ***, **, and * implies values significant at 1%, 5%, and 10%, respectively.*

4.5. Discussion

In this paper, seven hypotheses are tested and all of them received support from the data sample.

The first hypothesis *H1* is confirmed. The perceived risk (β = -0.226, p-value = 0.000) has a significantly negative impact on the behavioural intention to adopt AI technology in non-life insurers. To adopt AI technology, insurers must collect, handle, and store a huge amount of sensitive customer data, leading to several potential risks such as cyber-attacks and identity theft. Therefore, if the perceived risk increases by 1 unit, the behavioural intention to adopt AI technology in non-life insurers would decline by 0.226.

Secondly, the perceived self-efficacy of employees (β = 0.265, p-value = 0.000) has a positive influence on the perceived usefulness of AI technology. Additionally, if insurance companies create favorable conditions for their employees to improve their knowledge of AI technology, they would also easily use AI technology. Therefore, the third hypothesis *H3* is confirmed. Facilitating conditions positively affect the perceived ease of use of AI technology (β = 0.245, p-value = 0.000). If non-life insurers invest in technical and organizational infrastructures, the perceived ease of use of AI technology would be enhanced. This result is in line with Alam et al. (2020) and Islam et al. (2022).

According to Table 7, perceived ease of use positively influences the perceived usefulness of AI technology (β = 0.284, p-value = 0.000). User-friendly AI technology not only makes employees satisfied but also improves their performance, thus increasing their perceived usefulness.

As expected, perceived ease of use is found to be positively related to attitudes toward adoption, with a significant coefficient of nearly 0.3. If employees have excellent knowledge and skills in AI technology, they believe in their own ability to exploit the benefits of AI technology to enhance their working performance. Consequently, they tend to use AI technology frequently, thereby increasing their awareness of the usefulness of AI technology. In contrast, if employees do not know about AI technology, they will find it difficult to use AI technology. As a result, they will tend to use this technology infrequently, reducing their awareness of the usefulness of AI technology. It is consistent with the results of Hong (2022).

With regard to the effect of perceived usefulness, *H6* pertaining to the positive relationship between *PU* and *AT* toward behavioural intention to adopt AI technology is supported (β = 0.295, p-value = 0.000). In fact, if employees believe that AI technology is easy to use, their attitude towards adopting AI technology would be positive. Then, all staff members acquiesce to the application of technology in their daily tasks. Meanwhile, employees who believe that adopting AI technology is difficult have feelings of anxiety, leading to a negative attitude towards adopting AI technology. They might suppose that adopting AI technology is inefficient.

Finally, the hypothesized path of attitudes toward adoption and the behavioural intention to adopt AI technology is statistically significant ($\beta = 0.484$, p-value = 000). The strongest positive effect belongs to the attitudes toward adoption. When insurance companies plan to invest in AI technology, they would take the vote of employees. If most staff members believe that adopting AI technology is beneficial for their company, the behavioural intention to adopt AI technology would increase. On the contrary, if the majority of employees and managers argue that AI technology does not significantly improve their working efficiency, decreasing the behavioural intention to adopt AI technology in non-life insurers.

5. CONCLUSION

The adoption of AI technology brings various benefits to non-life insurance companies. This research proposes a structural model of factors influencing the adoption of AI technology in Vietnamese non-life insurers. Empirical results show that the behavioural intention to adopt AI technology is negatively impacted by perceived risk, consistent with Cukurova et al. (2020) and Horowitz and Kahn (2021). However, its coefficient is less than the coefficient of attitudes toward adoption, implying that perceived risk is not a serious issue for insurance companies. Attitudes toward adoption have the strongest effect on the behavioural intention to adopt AI technology, as suggested by Pham et al. (2022) and Na et al. (2023). Moreover, the paths from perceived usefulness and perceived ease of use to attitudes toward adoption are positively significant. Major insurance employees believe that adopting AI technology would improve their productivity and reduce operating expenses for insurers. Adopting AI technology also enhances the profits of insurance companies if their staff easily apply AI technology to their work. A positive relationship between perceived self-efficacy and perceived usefulness is confirmed, indicating that employees recognize the usefulness of AI technology. We also find a positive relationship between facilitating conditions and perceived ease of use. Hence, Vietnamese non-life insurers should create more and more facilitating conditions to encourage their employees to adopt AI technology.

Some implications could be drawn from the research results. Firstly, since perceived risk has a negative impact on the behavioural intention to adopt AI technology, Vietnamese non-life insurers should pay attention to potential risks in AI adoption. Sensitive client data must be acquired, processed, and stored in a way that complies with security laws, data privacy, and moral and ethical principles. Furthermore, the Department of the Insurance Supervisory Authority should establish legal frameworks for data management in insurance companies. Secondly, facilitating conditions and perceived ease of use are considered preconditions for a successful implementation of AI. Non-life insurers should invest a large amount of funds in building computer systems as well as modern software and applications. These AI applications should be tailored to meet employee preferences, increasing ease of use. Finally, a supportive learning environment where employees are encouraged to explore and experiment with AI applications should be built. Thanks to this environment, employees in insurance firms could collaborate productively with AI applications in their daily tasks such as customer interaction, underwriting, claim settlement, product offerings, etc.

There are several limitations in this paper. Firstly, due to limited time and means of communication, the data sample includes only 468 respondents. Secondly, the paper only examines factors effecting influencing the adoption of AI technology in Vietnamese non-life insurers. The life insurance firms are excluded. Finally, AI technology is relatively unfamiliar and has not been investigated much in Vietnam, leading to several confusions about questions of measurement in questionnaires.

As a result, some directions for further search are suggested. Firstly, expand the data sample to life insurers as well as the number of respondents. Secondly, in-depth interviews with professionals in the field of AI technology should be conducted to make questionnaires more transparent.

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