DETERMINANTS OF GENERATIVE ARTIFICIAL INTELLIGENCE ADOPTION IN INSURANCE COMPANIES

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ABSTRACT

This study aims to investigate the factors that influence the adoption of Generative artificial intelligence (GEN-AI) in insurance companies by utilizing the technology-organization-environment (TOE) framework. This study employs the TOE framework to examine the factors that impact the GEN-AI adoption at organizational level and was conducted on 307 insurance company managers and analysed using partial least squares (PLS). The research offers insurance companies and policy maker insights and recommendations for GEN-AI adoption. The empirical results reveal that relative advantage (RA), perceived compatibility (PC) and top management support (TMS) significantly influence GEN-AI adoption, CP, OR have positive effect on TMS, but perceived compatibility (PC) cannot significantly influence GEN-AI adoption. TMS mediates between competitive pressure（CP） and GEN-AI in insurance firms, and it also mediates between organizational readiness (OR) and GEN-AI. This study provides countermeasure advice to AI technology developers, insurance company manager, and practitioners.

***Keywords*:** Generative artificial intelligence, Insurance company, TOE framework.

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1. INTRODUCTION

Artificial intelligence (AI) is crucial for enhancing the productivity and efficacy of tasks (Javaid. et al., 2022), developing innovations (Bahoo et al., 2023), and strengthening the sustainability of businesses (Burger et al., 2023) and operating performance (Mariani et al., 2023; Yubo et al., 2022). GEN-AI has been one of the most complicated applications of AI. Artificial intelligence has become one of the most advanced technologies (Yubo et al., 2023). GEN-AI is characterized as an innovative technology with the ability to generate novel creative content in the form of texts, photographs, and videos (Mondal et al., 2023). This technology establishes new regulations in the digital content market, creating additional space and possibilities for creation (Burger et al., 2023). GEN-AI has been adopted in a variety of business and management sectors (Agrawal, 2024). GEN-AI uses machine learning and creative algorithms to expand its repository of knowledge (Aattouri et al., 2023). For example, ChatGPT, which relies on self-training and continuous learning (Mondal et al., 2023), is suitable for improving firm management and decision support systems. GEN-AI has revolutionized various businesses, resulting in rapid and efficient consumer services across all sectors.

AI reconfigures the boundaries and logic of insurance services (Deng et al., 2024; Wook, 2020); GEN-AI is deeply used in the core business of insurance companies, such as intelligent underwriting and claims and product analysis (Kapadiya et al., 2022; Owens et al., 2022). Chatbots and intelligent customer services are integral to insurance industries, and improving productivity is increasing considerably (Rodrigues et al., 2022).

Studies have shown that AI adoption by organizations is influenced by environment, organization, and technology factors (Pan et al., 2022; Smit et al., 2021), and the direct impacts of relative advantage (RA), perceived compatibility (PC), competitive pressure (CP), and organizational readiness (OR) on AI adoption have been explored (Min et al., 2024). However, prior research has focused less on its role as a mediating variable between different factors of TOE. There is a lack of extensive studies on the mediating influence of the TMS on GEN-AI adoption, specifically in relation to OR and CP.

Research suggests that AI adoption is significantly influenced by CP, the TMS, government support, and customer pressure (Chatterjee et al., 2021). Yuangao et al. (2023) reported that OR and perceived benefits are factors that influence AI usage in HR systems. AI can enhance the effectiveness of the HR system. Similar evidence is available in Na et al. (2022) and Das et al. (2023), who investigated the variables that affected the adoption of AI. Chen et al. (2020), through a survey of Chinese telecommunications companies, concluded that technological, organisational, and environmental factors have positive effects on organisations' adoption of AI. Sharma et al. (2023) reported that RPA adoption in service industries was influenced by factors such as low complexity, the establishment of a centre of excellence, and pressure from business partners. Given this context, this study has two objectives:

1) To investigate the elements that influence GEN-AI adoption in insurance firms.
2) To explore how the TMS mediates the relationship between GEN-AI adoption and insurance firms.

2. LITERATURE REVIEW

2.1. TOE framework

The TOE framework is a widely utilized framework for comprehending the process by which organizations adopt new technology (Thanabalan et al., 2024). This model offers a comprehensive framework for comprehending the essential issues that firms must consider while implementing and embracing technology (Sharma et al., 2023). The TOE framework stands out for its ability to offer precise insights and thorough forecasts regarding the elements that influence technology adoption. This is achieved by analysing the environmental, technological, and organizational variables in a complete manner (Hashimy et al., 2023). Although frequently applied, many studies concentrate on the direct influence that TOE has on the adoption of technology. This approach fails to take into account the interplay between factors, leading to an underestimation of their significance; therefore, we suggest that the TMS acts as an intermediary between organizational and environmental factors and GEN-AI adoption.

2.2. Hypothesis development

2.2.1 Relative advantage (RA)and Generative AI (GEN-AI)

RA is the degree to which a firm perceives an invention as being superior to its prior version (Nordin et al., 2022; Thong, 1999). RA was the TOE factor found to be significant in new technology adoption (Amin et al., 2024). Several studies have demonstrated that the advantages of introducing a new technology are directly related to AI usage (Baiod et al., 2024; Naeem et al., 2024). Within the realm of AI, the RA that technology offers to organizations has been identified as a crucial element influencing its adoption. (Phuoc, 2022; Pillai et al., 2021). Hence, we posit the following:

H1: RA positively affects GEN-AI adoption among insurance companies.

2.2.2 Perceived compatibility (PC) and Generative AI (GEN-AI)

PC is a concept that is defined and quantified to encompass the characteristics of both the technology and the organizational context (Shavneet et al., 2024). Van et al. (2024) suggested that the urge to implement blockchain technology is positively influenced by compatibility. The impact of TOE characteristics on big data adoption analytics was examined by Maroufkhani et al. (2023). They observe that compatibility has a significant role in BDA adoption. Seethamraju et al. (2023) reported that PC plays a role in AI adoption. Hence, we posit the following by utilizing the TOE framework:

H2: PC positively affects GEN-AI adoption among insurance companies.

2.2.3 Competitive pressure (CP) and top management support (TMS)

CP involves the collective forces exerted by rival companies within the same industry (Sun et al., 2020). Competitive pressure is recognized as one of the key factors driving top management support for new technology adoption (Maroufkhani et al., 2023). When firms face competitive pressures, top management is more likely to support new technologies with a view to improving the organization's competitiveness (Isiaku et al., 2024). Insurance companies face intense competition, and this pressure is driving top managers to place greater emphasis on technological innovation to improve operational efficiency (Al-khatib, 2023). Hence, we posit the following:

H3: CP positively affects top management support among insurance companies.

2.2.4 Organizational readiness (OR) and top management support (TMS)

OR encompasses the concrete and abstract resources that companies possess to facilitate the implementation of technology via procedures, processes, and programs (Al-khatib, 2023). Organizational readiness typically reflects whether a company has the technical resources and management systems necessary to implement a new technology implementation (Pathak et al., 2025). The organization has the infrastructure and training mechanisms in place, top management is more willing to commit resources to support the adoption of new technologies (Le et al., 2025). Hence, we posit the following:

H4: Organizational readiness positively affects the adoption of GEN-AIs among insurance companies.

2.2.5 Top management support (TMS) and Generative AI (GEN-AI)

TMS is defined as the extent to which the highest level of management incorporates, comprehends, and embraces advancements in technology. AI heavily relies on strong endorsement and backing from the TMS. This feature is well recognized in research as a crucial factor that affects AI adoption (Horani et al., 2023). New technology adoption is contingent upon the involvement of top management, as they hold the authority to make decisions (Al Halbusi et al., 2023; Hashimy et al., 2023). Top management coordinates the allocation of resources and offers financial and organizational assistance (Baig et al., 2023). Senior management's primary responsibility is to facilitate the integration of technology by providing continuous employee training (Iranmanesh. et al., 2023). Hence, we posit the following:

H5: TMS positively affects the adoption of GEN-AIs among insurance companies.

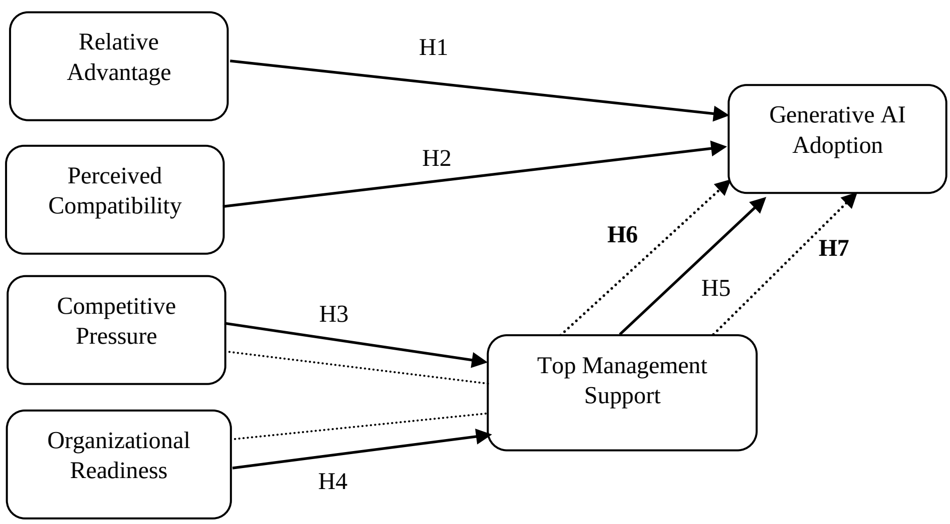
2.2.6 The Mediating Effect: Top management support

TMS is crucial for converting the features of the external environment into reactions by the company (Ngah et al., 2020). Mezghani et al. (2022) emphasize the importance of strong support from top management as a mediating factor that can aid in mitigating the impact of CP while implementing BDA. The deployment of big data analytics by competitors is expected to motivate top management to replicate similar methods. Moreover, the growing adoption of BDA by rivals and business partners is expected to exert coercive influence on senior executives to increase their capacity to gain market intelligence and maintain a competitive advantage with greater effectiveness and efficiency (Teo et al., 2003).

An essential prerequisite for top management to develop their stance on the extensive implementation of big data analytics inside an enterprise is organizational preparedness. Managers provide greater support when they are convinced that the company has the resources and the necessary competencies to facilitate the widespread adoption of big data analytics (Chen et al., 2015). Maroufkhani et al. (2023) verified that connections between the factors influencing BDA adoption, such as the impact of compatibility and the readiness of the organization, are influenced by the backing of top management. Hence, we posit the following:

H6: TMS mediates the relationship between CP and GEN-AI adoption among insurance companies.
H7: TMS mediates the relationship between OR and GEN-AI adoption in insurance companies.

Figure 1: Research Model



3. METHODOLOGY

3.1. Sample and data collection

The study employed a purposive sampling method and cross-sectional survey research to obtain the survey sample. The questionnaire was distributed online via QuestionnaireStar to the insurance industry at Chinese insurance companies. The survey was conducted from January to April 2024. The participants were filtered to guarantee that they met the study obligation. The sample includes top managers who influence the decision to adopt GEN-AI among insurance companies and who are familiar with company performance.

We created a questionnaire to test our hypotheses, and the questionnaire was evaluated by specialists in the GEN-AI and the insurance sector. At the same time, to evaluate the accuracy of the questions and guarantee that potential replies can deliver relevant answers, pretesting was undertaken in January 2024 with a sample of 30 participants. The preliminary survey findings prompted particular modifications to the final questionnaire in terms of language and punctuation. The primary survey and pilot of the study were completed in a timely manner, with a deliberate effort to minimize any time gap that could affect the study. The first part of the questionnaire consisted of demographic inquiries that were relevant to respondent basic information. The second segment was composed of components that were derived from the construct described in the research model. The questionnaire was used to determine the specific circumstances and objectives of this investigation. The questionnaire consists of 21 items generated from 6 components, and it also includes four demographic queries. The elements within each construct were randomly shuffled and lacked any specific order.

The respondents completed a total of 386 questionnaires. However, 79 of them were excluded because they did not meet the filter criteria. Therefore, the conclusive examination, which relied on 307 surveys, was ultimately concluded in February 2024. Table 1 provides a concise overview of the demographic characteristics.

Table 1: Demographic Information of Respondents

Characteristics Frequency (%) s		**Frequency**	**(%)**
Gender	Male	164	53.4%
	Female	143	46.6%
Age	≤ 20	13	4.2%
	20 < Age ≤30	93	30.3%
	30< Age ≤40	69	22.5%
	40< Age ≤50	55	17.9%
	50< Age ≤60	46	15.0%
	>60	31	10.1%
Education	Primary qualification	13	4.2%
	Secondary qualification	15	4.9%
	Diploma	43	14.0%
	Undergraduate degree	143	46.6%
	Master	71	23.1%
	PHD	22	7.2%
Position	Top management	118	38.4%
	Middle management	135	44.0%

	Administrators	54	17.6%
Company Age	Company Age < 10 years	122	39.7%
	10 ≤ Company Age < 20 years	53	17.3%
	20 ≤ Company Age < 30 years	55	17.9%
	30 ≤ Company Age < 40 years	65	21.2%
	Company Age ≥ 40 years	12	3.9%

3.2. Measures

As advised by Brislin (1980), to cope with the special circumstances of collecting data in China, we implemented the back-translation method; this approach verified that the measuring instruments were linguistic and culturally equivalent for all languages. The questionnaire was translated from English to Chinese and subsequently back to English by various foreign translators. Discrepancies were recognized and rectified for conceptual equivalence and content validity in Chinese. The backtranslation method facilitated precise and reliable data gathering in China, mitigating linguistic and cultural disparities while improving survey reliability and validity.
In this study, we utilized a 5-point Likert-type scale (1 = “strongly agree,” 3 = “neutral,” and 5 = “strongly disagree”). We used 5 items for RA following (Somya et al., 2022). All the PC items were borrowed from Al-khatib (2023). TMS following (Sharma et al., 2023) and CP from Chen et al. (2022). OR was measured from Pizam et al. (2022). GEN-AI adoption was measured from Shavneet et al. (2024). The measurement items are displayed in Table 2.

Table 2: Measurement Items

Constructs	Items	Item Statements	Source
Relative advantage	RA1	Insurance companies using GEN-AI can finish business activities more quickly.	
(RA)	RA2	Insurance companies using GEN-AI can increase operational efficiency.	
	RA3	Implementing GEN-AI in insurance companies has the potential to enhance their financial gains.	(Somya et al., 2022)
	RA4	Implementing GEN-AI in insurance companies has the potential to enhance their financial gains.	
	RA5	Introducing GEN-AI in insurance is advantageous for me to handle.	
Perceived compatibility	PC1	The utilization of GEN-AI is in accordance with the operations of our company.	
			(Al-khatib, 2023)
(PC)	PC2	Our company's infrastructure is designed to support and work well with GEN-AI technology.	

	PC3	The GEN-AI technology aligns with the objectives and organisational culture of our firm.	
Competitive Pressure	CP1	Our competitors are adopting GEN-AI technology.	
(CP)	CP2	The industry organization is requesting that our company implement GEN-AI technology.	(Yuangao et al., 2023)
	CP3	Our organization is compelled to implement GEN-AI technology due to competitive pressures.	
Organizational readiness	OR1	My firm has a high level of financial resources available to cover the costs of adopting GEN-AI.	
(OR)	OR2	In my company, there are many policies in place that foster the adoption of GEN-AI.	(Pizam et al., 2022)
	OR3	My company is very prepared for the implementation of GEN-AI overall.	
Top manager support	TMS1	The top managers are quite interested in adopting GEN-AI.	
(TMS)	TMS2	The benefits of GEN-AI for the future are acknowledged by top management.	
	TMS3	The top managers have allocated ample financial and other resources for the advancement and functioning of GEN-AI.	(Sharma et al., 2023)
	TMS4	The top management aims to position your organization as a frontrunner in the advancement of GEN-AI.	
	TMS5	The financial and organizational hazards that are associated with the use of GEN-AI are being accepted by the company's leadership.	
Generative AI adoption	GEN-AI1	Our business intends to use GEN-AI.	
(GEN-AI)	GEN-AI 2	In the future, our company plans to incorporate GEN-AI into our operations on a regular basis.	(Sharma et al., 2023)
	GEN-AI 3	We highly encourage GEN-AI for other firms to adopt.	
	GEN-AI4	Our company plans to utilize GEN-AI.	

GEN-AI5	In the future, our company plans to incorporate GEN-AI into our operations on a regular basis.

3.3. Checking common method bias (CMB)

To mitigate the potential impact of common method bias (CMB), we implemented various methodological strategies (Podsakoff et al., 2024). Primarily, we ensured that each response was kept anonymous to safeguard their identity. Consequently, social desirability diminishes, allowing participants to provide more objective responses. Furthermore, we employed statistical techniques, including Harman's single-factor test, to detect potential common approach bias issues. The single-factor test formulated by Harman was employed. Harman's test revealed that the single-factor variation constituted just 35% of the total variance, failing to meet the 50% criterion. This outcome suggests that CMB was not a substantial concern in the study (Harman, 1976).

4. DATA ANALYSIS

The models were analysed via PLS modelling, with the SmartPLS 4 version used as the statistical instrument. This approach was selected because of its independence from the assumption of normalcy, a condition that is seldom met in survey research (Chin et al., 2003). For common method bias, each variable will undergo regression analysis with a shared variable. A variance inflation factor (VIF) less than 3.3 indicates that there is no bias resulting from the use of a single source of data. The investigation revealed a maximum VIF of 1.659, which is below the threshold of 3.3 (Kock et al., 2012).

Table 3: Full-Collinearity Testing

Constructs	CP	GEN-AI	OR	PC	RA	TMS
VIF	1.305	1.659	1.477	1.111	1.513	1.407

4.1 Measurement Model

We conducted a measurement model assessment to evaluate the accuracy and consistency of the constructs utilized, in which the values of loadings should be $\geqslant 0.708$, the AVE should be $\geqslant 0.5$ and the CR should be $\geqslant 0.7$ (Hair et al., 2022; Ramayah et al., 2018).

First, we assessed the loadings, average variance extracted (AVE), and composite reliability (CR). As shown in Table 4, the AVE (the minimum value is 0.640) are all greater than 0.5, and the CR (the minimum value is 0.842) are all greater than 0.7. The loadings are all greater than 0.708 (the minimum value is 0.776) (Hair et al., 2022).

Furthermore, we evaluated discriminant validity by applying the HTMT (Henseler et al., 2015). The HTMT must adhere to a tighter requirement of being < 0.85, whereas the more liberal criterion requires them to be ⩽ 0.90. The data in Table 5 show that every HTMT measurement was lower than the more rigorous criterion of < 0.85 (with the highest value being 0.601). We conclude that the respondents thoroughly comprehended the fact that the six constructs were distinct from one another. The results of each of these validity tests have shown that the measuring items, when evaluated independently, contain both validity and reliability.

Table 4: Measurement Model

Constructs	**Items**	**Loadings**	**CR**	**AVE**
RA	RA1	0.829	0.911	0.671
	RA2	0.818		
	RA3	0.833		
	RA4	0.798		
	RA5	0.819		
PC	PC1	0.847	0.893	0.737
	PC2	0.817		
	PC3	0.909		
CP	CP1	0.857	0.867	0.685
	CP2	0.848		
	CP3	0.776		
OR	OR1	0.803	0.842	0.640
	OR2	0.777		
	OR3	0.819		
TMS	TMP1	0.806	0.914	0.681
	TMP2	0.829		
	TMP3	0.838		
	TMP4	0.844		
	TMP5	0.808		
GEN-AI	GEN-AI1	0.810	0.910	0.669
	GEN-AI2	0.824		
	GEN-AI3	0.829		
	GEN-AI4	0.790		
	GEN-AI5	0.835		

Table 5: Discriminant Validity (HTMT)

Constructs	**CP**	**GEN-AI**	**OR**	**PC**	**RA**	**TMS**
CP						
GEN-AI	0.484					
OR	0.508	0.601				
PC	0.181	0.251	0.319			
RA	0.407	0.564	0.520	0.309		
TMS	0.397	0.51	0.475	0.243	0.476	

Notes: RA=Relative advantage, PC=Perceived compatibility, CP=Competitive pressure, OR=Organizational readiness, TMS=Top manager support, GEN-AI=Generative AI adoption.

4.2 Structural Model

We provided the path coefficients, t values, standard errors, and p values for the structural model, as recommended by Hair et al. (2022) and Cain et al. (2017). The values were obtained via a resampling bootstrapping technique, with a sample size of 10,000 (Ramayah et al., 2018). Hahn and Ang (2017) recommended employing a variety of criteria, comprising p values, confidence intervals, and effect sizes, to evaluate the significance of a hypothesis. The results of the hypothesis testing of the direct effects are shown in Table 6.

We examined the impact of three predictors on GEN-AI. The R^2 value achieved was 0.323, suggesting that all three factors together accounted for 32.3% of the variability observed in GEN-AI. The value of TMS is 0.189, suggesting that the two factors accounted for 18.9% of the variability observed in TMS. RA ($\beta = 0.358$, $p < 0.01$), CP ($\beta = 0.222$, $p < 0.01$), OR ($\beta = 0.299$, $p < 0.01$), TMS ($\beta = 0.287$, $p < 0.01$), thus, H1, H3, H4 and H5 were supported. PC ($\beta = 0.083$, $p > 0.05$) was not significantly related to GEN-AI; thus, H2 was not supported.

To examine the mediation of the hypothesis, we followed the suggestion of Preacher et al. (2008) by utilizing bootstrapping to estimate the indirect effect. If the value of 0 is not included in the confidence interval, it can be deduced that there is a statistically substantial mediation effect. As shown in Table 6, CP → TMS → GEN-AI ($\beta = 0.064$, $p < 0.05$) and OR→ TMS → GEN-AI ($\beta = 0.086$, $p < 0.05$) were significant. The bias-corrected 95% confidence intervals did not include any values that straddled a zero. Thus, H6 and H7 were also supported.

Table 6: Hypothesis Testing Direct Effects

Hypotheses	Relationships	Path coefficient	STDEV	t-values	p-values	BCI LL	BCI UL	f^2	Discussion
H1	RA -> GEN-AI	0.358	0.057	6.227	0.000	0.247	0.472	0.150	Supported
H2	PC -> GEN-AI	0.068	0.046	1.480	0.139	-0.020	0.159	0.006	Not supported
H3	CP -> TMS	0.222	0.058	3.806	0.000	0.108	0.333	0.052	Supported
H4	OR -> TMS	0.299	0.059	5.080	0.000	0.182	0.412	0.094	Supported
H5	TMS -> GEN-AI	0.287	0.062	4.640	0.000	0.166	0.407	0.098	Supported
H6	CP -> TMS -> GEN-AI	0.064	0.022	2.963	0.003	0.028	0.112	0.005	Supported
H7	OR -> TMS-> GEN-AI	0.086	0.029	2.972	0.003	0.041	0.151	0.009	Supported

Notes: RA=Relative advantage, PC=Perceived compatibility, CP=Competitive pressure, OR=Organizational readiness, TMS=Top manager support, GEN-AI=Generative AI adoption.

PLS-predict is a method that was presented by Shmueli et al. (2019). Shmueli et al. (2019) suggested that if all the items of PLS-SEM_RMSE were lower than those of LM_RMSE, there was strong predictive power. If the majority PLS-SEM_RMSE is lower than LM_RMSE there is moderate predictive power. According to Table 7, the majority of PLS-SEM_RMSE values were lower than the LM_RMSE values. It is feasible to conclude that our model offers a moderate predictive potential.

Table7: PLS-Predict

Items	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-LM_RMSE
GEN-AI1	0.184	1.156	1.171	-0.015
GEN-AI2	0.201	1.196	1.209	-0.013
GEN-AI3	0.211	1.153	1.162	-0.009
GEN-AI4	0.187	1.157	1.156	0.001
GEN-AI5	0.221	1.14	1.145	-0.005

5. DISCUSSION

The results revealed that RA significantly influenced GEN-AI adoption, so H1 is supported. These findings indicate the importance of RA in GEN-AI adoption, which is consistent with the findings of previous studies (Al-khatib, 2023; Badghish et al., 2024). GEN-AI plays a role in various business processes of insurance companies, such as risk management, customer needs analysis, insurance product consultation, personalized recommendations of insurance products, automated underwriting, and customer communication. Companies can consider promoting GEN-AI only if they recognize its unique advantages over other technologies (Bin-Nashwan et al., 2025).

The results indicate that PC is not a significant factor in GEN-AI adoption, So H2 is not supported. The reason for this difference is that in technology adoption decisions, insurance companies may place more emphasis on the efficacy, cost-effectiveness and RA of GEN-AIs than on their compatibility with existing systems.

CP has a positive impact on the effect of TMS. So H3 is supported. This is consistent with (Dai et al., 2014),(Zhou et al., 2023),(Wiredu et al., 2024). Top managers who recognize that competitors are improving their competitiveness in the market by adopting new technologies, top managers will pay more attention to technology innovations in order to maintain the company's market position (Atta, 2024).

OR has a positive effect on top management support in insurance companies, so H4 is supported. Top management is more likely to show support for the adoption of new technologies if the organization has sufficient resources (Ali et al., 2024). They will recognize the potential and value of technology implementation. This support is not only in the form of providing the necessary resources, but also in the form of strategic facilitation and decision-making support.

It is found that the TMS significantly influences GEN-AI adoption, so H5 is supported. GEN-AI adoption often requires significant investment in hardware, software, training, etc., and the TMS provides the necessary funding and resources for GEN-AI adoption. The TMS ensures that these resources are prioritized and allocated. GEN-AI is a crucial skill that allows organizations to forecast their employees' objectives, aspirations, guidelines, and trajectory. This result aligns with the conclusions drawn from prior research on the acceptance of new technology.

GEN-AI adoption is significantly influenced by CP, which is mediated by the support of top management, thus H6 is supported. This suggests that when insurance companies face fierce market competition, to maintain a competitive advantage, CP will push top management to pay more attention to technical innovation and change and encourage the usage of technologies that are based on GEN-AI. Top management needs to flexibly adjust its resource allocation according to changes in CP to achieve technological innovation and business optimization to enhance market competitiveness and customer satisfaction. The results showed that the TMS acts as a mediator between OR and the adoption of GEN-Ais which confirms H7 is supported. This demonstrates that the TMS drives the transformation of organisational readiness and ensures the practical application of technology and resource readiness. Insurers can build on organisational readiness to better drive the adoption of GEN-AI through senior management support to enable technological innovation and business optimization.

5.1 Theoretical Contribution

This study provides new empirical data on GEN-AI adoption by insurance companies in China via a framework. These findings can be extrapolated to the specific population under investigation. Furthermore, the TOE framework is applied to evaluate GEN-AI adoption for Chinese insurance. The factors that influence GEN-AI adoption are explored to lay the groundwork for firms to utilize and promote GEN-AIs to improve efficiency and service delivery, thus bridging the gap between exploring the use of GEN-AIs at the firm level rather than from an individual's perspective. Third, this study demonstrated that TOE factors are interconnected and mutually influence one another. Our study findings demonstrate a correlation between technological variables and the TMS, with the TMS playing a significant role in elucidating the connection between technological elements and GEN-AI adoption. This study broadens the range of the theory of organizational effectiveness (TOE) by investigating the intermediary function of the TMS.

5.2 Practical Implications

First, as the role of RA is positive for the use of GEN-AI in the insurance industry, it is important for AI technology developers to focus on the importance of RA for AI adoption and to articulate the role of these types of technologies in the quality of service and business enhancement of companies, which will help them to recommend AI technologies to insurance companies and increase the rate of adoption.

Second, given the positive influence of the TMS on GEN-AI adoption, it is imperative for corporate managers in insurance companies to allocate resources and offer financial and institutional support. This incentivizes employees to embrace GEN-AI and ensures the availability of the infrastructure and tools required for its implementation. Additionally, fostering an organisational culture and structure that facilitates the integration and support of such technologies is crucial.

Third, since PC promotes the adoption of GEN-AI, it is important for AI technology developers to develop AI technology systems that are more compatible and improve the ease of use of this technology. Top managers should recognize the specificity of the insurance industry and continue to improve the fit of AI technology with the insurance company industry.
Fourth, the support of top management plays a mediating role in CP and GEN-AI. Top managers should fully recognize the complex competitive environment faced by the insurance industry and consider how to use AI technology to improve efficiency and service quality in the midst of fierce competition to cultivate the company's core competitiveness.

5.3 Limitations and Future Research

Although the study effectively accomplished its objectives, it is crucial to keep in mind that, like any other study, it additionally has specific constraints. First, this study focuses on insurance companies, and the next step is to spread the findings to other industries, such as manufacturing, and to examine the mediating effect of top manager support on technical and environmental factors. Second, this research aims to examine the impact of various unique TOE frameworks on GEN-AI adoption. Additional considerations include AI ethics, empathy, cost, and anthropomorphism. Subsequent investigations can expand upon our research by identifying additional drivers or moderating factors, thus yielding more comprehensive findings. Third, the theoretical framework of TOE was used in this study, and other theories, such as the diffusion of innovations theory, should be considered for application in the next step.

6. CONCLUSION

This study examines the factors influencing insurance companies GEN-AI adoption, including RA and PC, environmental factors such as CP, and organizational aspects such as OR and the TMS. We conducted this research through an on-survey, and the results show that RA and TM have a positive effect on GEN-AI, TMS mediates CP and GEN-AI, and TMS mediates OR and GEN-AI. Our study extends the TOE theory that the TMS is critical for generative AI adoption. In the face of increasing competition, top managers can realize that GEN-AI can enhance the market competitiveness of insurance companies and strengthen the organization's readiness in terms of talent development and technological infrastructure, thus facilitating the implementation of AI technology in the company.

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REFERENCES

Aattouri I., Mouncif H., & Rida M. (2023). Modeling of an artificial intelligence based enterprise callbot with natural language processing and machine learning algorithms. *International Journal of Artificial Intelligence, 12*(2), 943. doi:10.11591/ijai.v12.i2.pp943-955

Agrawal K. (2024). Towards Adoption of Generative AI in Organizational Settings. *Journal of Computer Information Systems, 64*(5), 636-651. doi:10.1080/08874417.2023.2240744

Al-khatib A. W. (2023). Drivers of generative artificial intelligence to fostering exploitative and exploratory innovation: A TOE framework. *Technology in Society, 75*(2), 12. doi:10.1016/j.techsoc.2023.102403

Al Halbusi H., Klobas J. E., & Ramayah T. (2023). Green core competence and firm performance in a post-conflict country, Iraq. *Business Strategy and the Environment, 32*(6), 2702-2714. doi:10.1002/bse.3265

Ali S. S., Kaur R., Gupta H., Ahmad Z., & Elnaggar G. (2024). Determinants of an Organization's Readiness for Drone Technologies Adoption. *Ieee Transactions on Engineering Management, 71*, 43-57. doi:10.1109/tem.2021.3083138

Amin A., Bhuiyan M. R. I., Hossain R., Molla C., Poli T. A., & Milon M. N. U. (2024). The adoption of Industry 4.0 technologies by using the technology organizational environment framework: The mediating role to manufacturing performance in a developing country. *Business Strategy and Development, 7*(2), 363. doi:10.1002/bsd2.363

Atta A. A. B. (2024). Adoption of fintech products through environmental regulations in Jordanian commercial banks. *Journal of Financial Reporting and Accounting, 13*(2), 14. doi:10.1108/jfra-09-2023-0507

Badghish S., & Soomro Y. A. (2024). Artificial Intelligence Adoption by SMEs to Achieve Sustainable Business Performance: Application of Technology-Organization-Environment Framework. *Sustainability, 16*(5), 24. doi:10.3390/su16051864

Bahoo S., Cucculelli M., & Qamar D. (2023). Artificial intelligence and corporate innovation: A review and research agenda. *Technological Forecasting and Social Change, 188*, 122264. doi:10.1016/j.techfore.2022.122264

Baig M. I., Yadegaridehkordi E., & Nizam Bin Md Nasir M. H. (2023). Influence of big data adoption on sustainable marketing and operation of SMEs: a hybrid approach of SEM-ANN. *Management Decision, 61*(7), 2231-2253. doi:10.1108/Md-06-2022-0778

Baiod W., & Hussain M. M. (2024). The impact and adoption of emerging technologies on accounting: perceptions of Canadian companies. *International Journal of Accounting and Information Management, 32*(4), 557-592. doi:10.1108/ijaim-05-2023-0123

Bin-Nashwan S. A., Li J. Z., Jiang H. C., Bajary A. R., & Ma'aji M. M. (2025). Does AI adoption redefine financial reporting accuracy, auditing efficiency, and information asymmetry? An integrated model of TOE-TAM-RDT and big data governance. *Computers in Human Behavior Reports*, *17*(3), 14. doi:10.1016/j.chbr.2024.100572

Brislin R. W. (1980). Cross-cultural research methods: Strategies, problems, applications. In *Environment and culture* (pp. 47-82): Springer.

Burger B., Kanbach D. K., Kraus S., Breier M., & Corvello V. (2023). On the use of AI-based tools like ChatGPT to support management research. *European Journal of Innovation Management, 26*(7), 233-241. doi:10.1108/EJIM-02-2023-0156

Cain M. K., Zhang Z., & Yuan K.-H. (2017). Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior research methods, 49*, 1716-1735. doi:10.3758/s13428-016-0814-1

Chatterjee S., Rana N. P., Dwivedi Y. K., & Baabdullah A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change, 170*(12), 14. doi:10.1016/j.techfore.2021.120880

Chen D. Q., Preston D. S., & Swink M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems*, *32*(4), 4-39. doi:10.1080/07421222.2015.1138364

Chen H., Li L., & Chen Y. (2020). Explore success factors that impact artificial intelligence adoption on telecom industry in China. *Journal of Management Analytics, 8*(1), 36-68. doi:10.1080/23270012.2020.1852895

Chen Y., Hu Y., Zhou S., & Yang S. (2022). Investigating the determinants of performance of artificial intelligence adoption in hospitality industry during COVID-19. *International Journal of Contemporary Hospitality Management*, *35*(8), 2868-2889. doi:10.1108/ijchm-04-2022-0433

Chin W. W., Marcolin B. L., & Newsted P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189-217. doi:10.1287/isre.14.2.189.16018

Dai J., Montabon F. L., & Cantor D. E. (2014). Linking rival and stakeholder pressure to green supply management: Mediating role of top management support. *Transportation Research Part E-Logistics and Transportation Review, 71*, 173-187. doi:10.1016/j.tre.2014.09.002

Das S. D., & Bala P. K. (2023). What drives MLOps adoption? An analysis using the TOE framework. *Journal of Decision Systems, 33*(3), 376-412. doi:10.1080/12460125.2023.2214306

Deng S. C., Zhang J. J., Lin Z. N., & Li X. Q. (2024). Service staff makes me nervous: Exploring the impact of insecure attachment on AI service preference. *Technological Forecasting and Social Change, 198*(13), 89-93. doi:10.1016/j.techfore.2023.122946

Hair J. F., Hult G. T. M., Ringle C. M., Sarstedt M., Danks N. P., & Ray S. (2022). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*: Springer Nature.

Harman H. H. (1976). *Modern factor analysis*: University of Chicago press.

Hashimy L., Jain G., & Grifell-Tatjé E. (2023). Determinants of blockchain adoption as decentralized business model by Spanish firms–an innovation theory perspective. *Industrial Management Data Systems, 123*(1), 204-228. doi:10.1108/IMDS-01-2022-0030

Henseler J., Ringle C. M., & Sarstedt M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science, 43*(1), 115-135. doi:10.1007/s11747-014-0403-8

Horani O. M., Al-Adwan A. S., Yaseen H., Hmoud H., Al-Rahmi W. M., & Alkhalifah A. (2023). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development, 12*(6), 25. doi:10.1177/02666669231166889

Iranmanesh., Lim K. H., Foroughi B., Hong M. C., & Ghobakhloo M. (2023). Determinants of intention to adopt big data and outsourcing among SMEs: organisational and technological factors as moderators. *Management Decision, 61*(1), 201-222. doi:10.1108/md-08-2021-1059

Isiaku L., & Adalier A. (2024). Determinants of business intelligence systems adoption in Nigerian banks: The role of perceived usefulness and ease of use. *Information Development*, 21. doi:10.1177/02666669241307024

Javaid., Haleem A., Singh R. P., & Suman R. (2022). Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study. *Journal of Industrial Integration and Management-Innovation and Entrepreneurship, 7*(1), 83-111. doi:10.1142/s2424862221300040

Kapadiya K., Patel U., Gupta R., Alshehri M. D., Tanwar S., Sharma G., & Bokoro P. N. (2022). Blockchain and AI-Empowered Healthcare Insurance Fraud Detection: an Analysis, Architecture, and Future Prospects. *Ieee Access, 10*, 79606-79627. doi:10.1109/access.2022.3194569

Kock N., & Lynn G. S. (2012). Lateral Collinearity and Misleading Results in Variance-Based SEM: An Illustration and Recommendations. *Journal of the Association for Information Systems, 13*(7), 546-580. doi:10.17705/1jais.00302

Le L. T. N., Jeenanunta C., Ueki Y., Intalar N., & Komolavanij S. (2025). The Role of Managerial Competencies in Driving Industry 4.0 Adoption: A Comparative Study of Thailand and Vietnam's Manufacturing Sectors. *Sustainability, 17*(1), 28. doi:10.3390/su17010077

Mariani M. M., Machado I., Magrelli V., & Dwivedi Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation*, *122*, 102623. doi:10.1016/j.technovation.2022.102623

Maroufkhani P., Iranmanesh M., & Ghobakhloo M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems, 123*(1), 278-301. doi:10.1108/imds-11-2021-0695

Mezghani K., Alsadi A. K., & Alaskar T. H. (2022). Study of the environmental factors' effects on big data analytics adoption in supply chain management. *International Journal of E-Business Research*, *18*(1), 1-20. doi:10.4018/IJEBR.309395

Min S., & Kim B. (2024). Adopting Artificial Intelligence Technology for Network Operations in Digital Transformation. *Administrative Sciences, 14*(4), 70. doi:10.3390/admsci14040070

Mondal S., Das S., & Vrana V. G. (2023). How to bell the cat? A theoretical review of generative artificial intelligence towards digital disruption in all walks of life. *Technologies, 11*(2), 44.

Na S., Heo S., Han S., Shin Y., & Roh Y. (2022). Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology-Organisation-Environment (TOE) Framework. *Buildings*, *12*(2), 17. doi:10.3390/buildings12020090

Naeem S., Azam M., Boulos M. N. K., & Bhatti R. (2024). Leveraging the TOE Framework: Examining the Potential of Mobile Health (mHealth) to Mitigate Health Inequalities. *Information, 15*(4), 176. doi:10.3390/info15040176

Ngah A. H., Ramayah T., Ali M. H., & Khan M. I. (2020). Halal transportation adoption among pharmaceuticals and comestics manufacturers. *Journal of Islamic Marketing, 11*(6), 1619-1639. doi:10.1108/jima-10-2018-0193

Nordin S. M., Zolkepli I. A., Rizal A. R. A., Tariq R., Mannan S., & Ramayah T. (2022). Paving the way to paddy food security: A multigroup analysis of agricultural education on Circular Economy Adoption. *Journal of Cleaner Production, 375*, 9. doi:10.1016/j.jclepro.2022.134089

Owens E., Sheehan B., Mullins M., Cunneen M., Ressel J., & Castignani G. (2022). Explainable Artificial Intelligence (XAI) in Insurance. *Risks, 10*(12), 230. doi:10.3390/risks10120230

Pan Y., Froese F., Liu N., Hu Y. Y., & Ye M. L. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *International Journal of Human Resource Management, 33*(6), 1125-1147. doi:10.1080/09585192.2021.1879206

Pathak A., & Bansal V. (2025). Technology or Organization: What is More Important for Artificial Intelligence Adoption? *Tehnicki Glasnik-Technical Journal, 19*(1), 136-141. doi:10.31803/tg-20240512171214

Phuoc N. V. (2022). The critical factors impacting artificial intelligence applications adoption in Vietnam: a structural equation modeling analysis. *Economies, 10*(6), 129. doi:10.3390/economies10060129

Pillai R., Sivathanu B., Mariani M., Rana N. P., Yang B., & Dwivedi Y. K. (2021). Adoption of AI-empowered industrial robots in auto component manufacturing companies.

Production Planning & Control, 33(16), 1517-1533. doi:10.1080/09537287.2021.1882689

Pizam A., Ozturk A. B., Balderas-Cejudo A., Buhalis D., Fuchs G., Hara T., . . . Chaulagain S. (2022). Factors affecting hotel managers' intentions to adopt robotic technologies: A global study. *International Journal of Hospitality Management, 102*(5), 15. doi:10.1016/j.ijhm.2022.103139

Podsakoff P. M., Podsakoff N. P., Williams L. J., Huang C., & Yang J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of Organizational Psychology Organizational Behavior, 11*(1), 17-61. doi:10.1146/annurev-orgpsych-110721-040030

Preacher K. J., & Hayes A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior research methods, 40*(3), 879-891. doi:10.3758/BRM.40.3.879

Ramayah T., Cheah J., Chuah F., Ting H., & Memon M. A. (2018). Partial least squares structural equation modeling (PLS-SEM) using smartPLS 3.0. *An updated guide practical guide to statistical analysis, 1*(1), 1-72.

Rodrigues A. R. D., Ferreira F. A., Teixeira F. J., & Zopounidis C. (2022). Artificial intelligence, digital transformation and cybersecurity in the banking sector: A multi-stakeholder cognition-driven framework. *Research in International Business Finance Research Letters, 60*(8), 30-41. doi:10.1016/j.ribaf.2022.101616

Seethamraju R., & Hecimovic A. (2023). Adoption of artificial intelligence in auditing: An exploratory study. *Australian Journal of Management, 48*(4), 780-800. doi:10.1177/03128962221108440

Sharma C., Bharadwaj S. S., Gupta N., & Jain H. (2023). Robotic process automation adoption: contextual factors from service sectors in an emerging economy. *Journal of Enterprise Information Management, 36*(1), 252-274. doi:10.1108/jeim-06-2021-0276

Shavneet S., & Gurmeet S. (2024). Why Do SMEs Adopt Artificial Intelligence-Based Chatbots? *Ieee Transactions on Engineering Management, 71*, 1773-1786. doi:10.1109/tem.2022.3203469

Shmueli, Sarstedt M., Hair J. F., Cheah J. H., Ting H., Vaithilingam S., & Ringle C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322-2347. doi:10.1108/ejm-02-2019-0189

Smit D., Eybers S., & Smith J. (2021, Dec 06-10). *A Data Analytics Organisation's Perspective on Trust and AI Adoption.* Paper presented at the 2nd Southern African Conference forArtificial Intelligence Research (SACAIR), Ctr AI Res, ELECTR NETWORK.

Somya G., Wafa G., Dharen K. P., & Sah G. P. (2022). Artificial intelligence adoption in the insurance industry: Evidence using the technology-organization-environment framework. *Research in International Business and Finance, 63*(8), 15. doi:10.1016/j.ribaf.2022.101757

Sun S., Hall D. J., & Cegielski C. G. (2020). Organizational intention to adopt big data in the B2B context: An integrated view. *Industrial Marketing Management, 86*, 109-121. doi:10.1016/j.indmarman.2019.09.003

Teo H. H., Wei K. K., & Benbasat I. (2003). Predicting intention to adopt interorganizational linkages: An institutional perspective. *Mis Quarterly, 27*(1), 19-49. doi:10.2307/30036518

Thanabalan P., Vafaei-Zadeh A., Hanifah H., & Ramayah T. (2024). Big Data Analytics Adoption in Manufacturing Companies: The Contingent Role of Data-Driven Culture. *Information Systems Frontiers*, 27. doi:10.1007/s10796-024-10491-0

Thong J. Y. (1999). An integrated model of information systems adoption in small businesses. *Journal of Management Information Systems, 15*(4), 187-214.

Van L., Truong H. T. H., Vo-Thanh T., Nguyen H. T. T., Dang-Van T., & Nguyen N. (2024). Determinants of blockchain technology adoption in small and medium hospitality and tourism enterprises. *Journal of Hospitality Marketing & Management, 33*(7), 867-897. doi:10.1080/19368623.2024.2335931

Wiredu J., Yang Q., Sampene A. K., Gyamfi B. A., & Asongu S. A. (2024). The effect of green supply chain management practices on corporate environmental performance: Does supply chain competitive advantage matter? *Business Strategy and the Environment, 33*(3), 2578-2599. doi:10.1002/bse.3606

Wook J. J. (2020). Case Studies for Insurance Service Marketing Using Artificial Intelligence(AI) in the InsurTech Industry. [인슈어테크(InsurTech)산업에서의 인공지능(AI)을 활용한보험서비스 마케팅사례 연구]. *Journal of Digital Convergence*, *18*(10), 175-180. doi:10.14400/jdc.2020.18.10.175

Yuangao C., Hu Y., Zhou S., & Yang S. (2023). Investigating the determinants of performance of artificial intelligence adoption in hospitality industry during COVID-19. *International Journal of Contemporary Hospitality Management, 35*(8), 2868-2889. doi:10.1108/IJCHM-04-2022-0433

Yubo S., Ramayah T., & Hongmei L. (2022). Research on the Impact of Intelligent Manufacturing Technology on Business Model Based on CNKI's Evidence. *Global Business & Management Research, 14*, 266-283.

Yubo S., Ramayah T., Hongmei L., Yifan Z., & Wenhui W. (2023). Analysing the current status, hotspots, and future trends of technology management: Using the WoS and scopus database. *Heliyon, 9*(9), 7-29. doi:10.1016/j.heliyon.2023.e19922

Zhou B. R., & Zheng L. (2023). Technology-pushed, market-pulled, or government-driven? The adoption of industry 4.0 technologies in a developing economy. *Journal of Manufacturing Technology Management, 34*(9), 115-138. doi:10.1108/jmtm-09-2022-0313