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Research on the Risk Management Mechanism of Technological Innovation Investment under the Background of Artificial Intelligence Development: An Insurance Mechanisms Perspective

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Abstract: This study investigates the risk management mechanisms influencing technological innovation investments in the context of artificial intelligence (AI) development. A quantitative approach was employed, using a structured survey distributed to 300 firms involved in AI-driven innovation across various industries, including healthcare, finance, manufacturing, and technology. The data were analyzed using regression and structural equation modeling (SEM) techniques. The findings reveal that technological uncertainty can positively impact investment success when firms effectively manage risks, with a mean score of 4.2 for technological uncertainty and 3.9 for investment success. In contrast, market risks (mean = 3.6) and regulatory challenges (mean = 3.7) negatively affect outcomes. Additionally, the study highlights the critical role of risk management mechanisms (mean = 4.0) and organizational readiness in moderating these risks. Firms with robust risk management practices and higher organizational preparedness are more likely to achieve successful AI-driven investments. These results contribute to the growing literature on AI-driven innovation by emphasizing the importance of risk management and internal capabilities in navigating the complexities of AI investment.

Keywords: AI-driven innovation; market risks; organizational readiness; risk management; technological innovation investments; technological uncertainty

1 INTRODUCTION

In recent years, the application of AI has expanded across industries globally, driving the emergence of new technological opportunities and transforming investment market dynamics [1]. As a technology capable of emulating human intelligence through learning, problem-solving, and decision-making, AI is considered a powerful catalyst for economic and technological change. It has been integrated into various fields such as healthcare, finance, production, and supply chains, spurring significant investments in AI technologies [2]. While the potential for AI-driven innovation is vast, it also introduces diverse risks that must be understood and managed to sustain this innovation. Effective risk management in technological innovation investment is crucial for businesses operating in constantly changing environments. Technological contingencies, particularly those related to AI investments, are subject to uncertainties stemming from fluctuating technological processes, dynamic regulatory requirements, market trends, and cyber-attack risks [3]. These risks are further complicated by the fact that AI technologies are still emerging, evolving, and being refined [4]. This is why the issue of effective risk management is probably more acute now than at any time in the past. At present, firms are exposed to two sources of risk: technological risk and financial risk.

Hence, this paper aims at analyzing the risk management framework for investment in technological innovation based on the context of the development of AI technology [5]. It seeks to present the broad framework that will enable organizations to cater for risks inherent in the unfolding AI led technological advancement both outside the organization; market risks including but not limited to changes in legislation and market trends as well as internal risks including the readiness of the organization for the technological advancement and its feasibility. The following discusses some of the main issues affecting investment in technological innovation and the effect of AI in increasing or decreasing the risk posed by these issues [6]. Technological innovation investments are relatively expensive and involve certain risks since the development of technologies is uncertain, and so are the markets. Old techno-commercial logics refer to profound capital expenses and long product-development cycles with outcome-declining market returns [7]. There is technological uncertainty, which is the degree of future technological change that a specific technology path produces and its impact on the existing structure of competition. These uncertainties are further accelerated by the high rate of AI advancement, which is Industry 4.0's key characteristic. AI technologies usually develop much faster than their regulatory and market frameworks [8].

Thus, one of the significant threats of the introduction of AI into new developments is market risk, coupled with technological uncertainty. The market demand for using some AI technologies on the other hand can be very unpredictable and may vary with the state of the economy, changes in customer trends and existence of similar products by other firms [9]. Market risk adds up to the discussion as most AI innovations are still in the experimental stages and many have not proven to work in the commercial market. It enhances the prospect of incurring costs upon the firm if an innovation or piece of AI does not sell or if the technology becomes outdated by newer advances [10]. There is also another general risk that is worth to be mentioned and it is a regulatory risk. As AI technologies unfold, the governments and regulatory organizations globally are struggling to determine how to address AI created innovations to achieve the appropriate levels that are ethical in the consumption globally and protect consumer privacy while preventing anti-competitive behaviors. Lack of specific guidelines gives some legal risks for investors or firms, and possible costs associated with compliance [5]. For instance, in the health and finance sectors where AI is applied in decision making processes that affect people's lives major risks face regulatory approval, thus enhancing the risk management process [11].

Consequently, while there are numerous considerations regarding AI technology, there are also tools that can be employed to manage the risks inherent in technological innovation investments. The use of AI can significantly enhance risk management by adding value to predictive analytics and decision-making tools, as well as extending value more effectively than other resources [12]. For instance, big data and business analytics can alert investors in real-time to market trends, consumer behaviors, and potential threats. Within the technological framework, AI can conduct risk analyses to identify risks related to new technology implementation, competitive factors, and the likelihood of legal constraints. Machine learning algorithms can uncover patterns and trends in large datasets from previous innovation projects, aiding in decisions about further investment [13]. These insights help investors determine the success probabilities of AI-integrated innovations based on market receptiveness, technological advancement, and demand. Moreover, AI can be utilized to create dynamic risk management frameworks that adapt to external environmental changes. Unlike traditional models that rely solely on historical data, AI-based models can dynamically adjust risk assessments when provided with real-time data [14]. This enables firms to respond promptly to new threats such as regulatory changes or technological breakthroughs. In this way, AI enhances the adaptability of innovation capital expenditure management and ensures successful functioning in the modern AI-oriented environment.

The article is structured as follows: the first section presents the background of the study, the significance of AI-driven technological innovation investments, and the associated risks. It also outlines the research objectives and the structure of the paper. Literature Review discusses the existing literature on AI development, technological innovation investments, and risk management. It highlights the gaps in the current research and sets the foundation for the study. Section 3 describes the research design, data collection process, sampling technique and sample size, data analysis techniques, and ethical considerations. Followed by it, findings show the descriptive statistics, correlation matrix, regression analysis, mediation and moderation analysis, latent variables analysis, model fit indices, factor analysis, and hypothesis testing summary. Section 5 interprets the findings, discusses their implications for practice, and highlights the main contributions of the research to the understanding of risk management mechanisms for AI-driven technological innovation investments. Finally, the Conclusion section summarizes the study's contributions and suggests specific directions for future research in the field of AI-driven innovation investments. It also acknowledges the limitations of the study and proposes areas for further research.

2 LITERATURE REVIEW

AI has revolutionized technological advancement and brought the prevalent risk evaluation criteria of investment into sharp focus. Indeed, contemporary literature abounds with detailed explorations of the opportunities and risks associated with AI-led advancements across various technologies [15]. However, the processes of mitigating these risks in investment, particularly in the volatile context of dynamic technological developments driven by internal and external market demands, have not been as extensively elaborated. This literature review concentrates on the relationship between AI development, technological innovation investment, and risk management, based on the current theoretical and empirical understanding of the issue. Technological innovation, a well-known driver of economic growth and competitiveness improvement [16], is often framed within the disruptive technology model. This model is characterized by new technologies that disrupt existing industries and create new growth opportunities. Such innovations are typically marked by high risks due to the uncertain impacts of technological changes. In the context of AI, this unpredictability is further magnified by the relatively high level of innovation in AI technologies, which are still in their pilot phase [17]. Technological changes driven by AI present both threats and challenges to investors and firms engaged in technological disruption within business systems and markets.

Thus, AI-based technologies pose specific risks observed on the topic of more commonly discussed technologies. A key set up risk in this case concerns technological uncertainty which is defined as the unpredictability of the path of the applicant technology (in this instance AI) and the likely impact this will have on existing technologies [18]. AI technologies are defined by the fact that they are self-developing as well as self-improving meaning that the functions that they undertake can become optimized over time as they carry out an analysis of more data. But it also indicates that the process of development of these AI technologies is highly incremental and involves a lot of trials and errors, and the results are unpredictable. This gives rise to a high-risk aspect for investors, which revolve around venture financing that may not culminate in good market returns, or when the technology taken to invest in, is replaced by other improved types on the block [19]. Furthermore, one aspect critical for decision making for AI-Driven innovation investment is market uncertainty. This is as close as the technological shifts are characterized by oscillating market forces because the market may respond to new technologies by offering varying demands. Disrupted industries are more sensitive to market fluctuations than more traditional industries, and AI technologies are nothing if not disruptive. For instance, AI adoption in Health care and Financial sectors as discussed earlier has elicited ethical and regulatory issues that in one way or the other influences the market acceptance and therefore the demand. In addition, the purchasing and selling of AI technologies turned out to have weak business models for AI products since there remains a challenge of how and where organizations can generate revenues from AI implementations [20]. This, by and large, gives rise to important risks to investors, who can suffer important technological losses if the guaranteed AI technologies are not a success on the market.

However, regulatory uncertainty poses a significant risk for AI-driven innovations when investing in technologies and markets. The legal guidelines governing AI applications remain underdeveloped, as governments and regulatory authorities worldwide have yet to fully establish frameworks that regulate and promote the ethical use of AI [21]. This is particularly evident in industries where AI is deployed in decision-making tasks, such as healthcare, finance, and automotive manufacturing. In these sectors, AI algorithms must be regulated to ensure they do not infringe upon consumer rights, discriminate against individuals, or deny fairness. However, the missing rules make investments insecure regarding legal risks and compliance expenses [22]. Therefore, regulatory risk forms part of the risk management mechanisms for AI-driven technological innovation investments.

Albeit the high risk related to AI generated innovations, the existing literature points to the application of AI in improving risk management of technological innovations investments. It is evident that AI has the potential to develop subsequent predictive analytics, refine choice making procedures, and advance resource utilization in managing risks [23]. Due to the use of AI, predictive analytics can offer investors immediate information regarding potential patterns or shifts in the market or consumers thus help the investors make more viable decisions [10]. AI-based risk management frameworks can also undertake real-time risk assessments that adapt to changes in the external environment including in the regulatory environment or in technological advances [5]. This makes it easier for firms to adapt to certain risks as they emanate thus improving on the firm's flexibility in the face of certain risks. However, the adoption of new AI advanced risk management mechanisms has not been easy to achieve. First, there is an issue of data quality and access. AI generative models require large datasets for analysis and prediction. However, in many industries, AI-driven innovation data may be lacking or imprecise [24]. Organizations need clean, interference-free data that also addresses privacy and security to apply AI in risk management. Furthermore, the opacity of many AI algorithms complicates transparency and accountability in risk management. Models like deep learning are "black boxes," so firms cannot know the basis of the risk assessments they generate or guarantee these assessments match their investment goals [25].

Another issue that is associated with the adoption of AI-driven risk management mechanisms is organizational readiness. The worry that emerges from the facts above is that deploying AI technologies is something that alters the existing structure, culture and skills of many firms, according to Lai et al., (2024) [26]. But firms need to acquire the necessary structures which include data storage and processing and talents for analyzing the insight gained from AI. This is even more demanding especially to small and medium-sized enterprises (SMEs) who might not afford to spend a lot of money in developing advanced AI systems. The literature indicates that AI implementations must be done in an organized manner; that the ability to implement AI is a competence that needs to be developed and that AI solutions must fit within the general risk management strategies of firms [27]. The literature also underscores the call for explainable AI (XAI) models for more interpretability and explain ability in the risk management process. XAI is the scientific area that aims to provide human intelligibility of AI solutions, that is, to explain how the AI system works and the results it returns [28]. This is particularly crucial with risk management where firms required to be sure that the results given are the correct ones with respect to the needed risk tolerance. In particular, the creation of XAI models is viewed as a step towards meeting the challenges of algorithmizing and improving the credibility of AI-dependent risk management systems [29].

3 METHODS

3.1 Research Design

This study adopted a quantitative research design to examine the risk management mechanisms associated with technological innovation investment within the context of artificial intelligence (AI) development. The quantitative approach was deemed most appropriate due to its ability to systematically analyze numerical data and uncover relationships between key variables, such as technological uncertainty, market risks, regulatory factors, and investment outcomes. The study utilized a cross-sectional design, capturing data at a single point in time from a wide range of firms and investors involved in AI-driven technological innovation. The design allowed for a comprehensive examination of the risk factors and the effectiveness of existing risk management strategies across diverse industry sectors. Given the dynamic and evolving nature of AI technologies, this design provided a snapshot of current practices, challenges, and successes in risk management, offering valuable insights for future research and practical applications.

3.2 Data Collection Process

The data for this research was collected through both primary and secondary methods. Secondary data was sourced from literature covering AI advancements from the perspectives of firms, investors, and risk management practitioners. The survey, designed with input from prior empirical work on risk management, innovation, and AI, used Likert-scale questions to gauge respondents' views on technological, market, and regulatory risks and their management. The questionnaire was pre-tested on a small group to check its reliability and validity. Secondary data also came from trade magazines, financial statements, government publications, and databases, offering insights into industry activities, environments, and AI-related legal aspects. This combination of primary and secondary data helped understand respondents' attitudes and the real market position of AI risks in technological innovation.

3.3 Sampling Technique and Sample Size

This study employed a purposive sampling technique to ensure that the sample consisted of firms and investors directly involved in AI-driven technological innovation. The purposive approach was appropriate given the specialized nature of the subject matter, where only certain individuals and organizations possessed the requisite knowledge and experience to provide meaningful insights. The sample included executives, risk managers, innovation leads, and financial professionals from companies actively investing in or developing AI technologies. Additionally, the sample incorporated regulatory professionals to gain a perspective on how regulatory risks were perceived and managed. A target sample size of 300 respondents was deemed sufficient to achieve statistical power and generalizability. This number was based on the assumption that a diverse range of firms would be represented, which includes small and medium enterprises (SMEs) and large multinational corporations, as well as firms from various industry sectors such as healthcare, finance, manufacturing, and technology. Given the focus on AI, the sample also included early-stage startups at the forefront of AI innovation, alongside more established firms with a significant stake in AI technologies.

3.4 Data Analysis Techniques

The survey data were quantitatively analyzed using different methods to give the results. The authors first used frequencies and percentages with means to describe the sociodemographic and organizational profiles of the respondents. These included risk frequency percentage, risk percentage, mean and standard deviation that aid in establishing the proportionate composition of the research sample and general trend of risk management practices across the industry. Descriptive statistics were then followed by inferential statistics in testing the study hypotheses. Linear regression analysis was used to identify dependencies of technological uncertainty and market risks as well as regulatory uncertainty and efficiency of risk management tools. Standard multiple regression analyses were conducted to examine the role and statistical relationship of various independent risk factors in the dependent variable of successful AI technological innovation investments. The method of moderation analysis was also used to assess variables including size, industry type and geographical location within which the risk factors influenced investment results. From this, it was possible to gain an understanding of how contexts influenced risk in AI-driven innovation investment. Furthermore, structural equation modeling (SEM) was incorporated into the study to evaluate the estimation of the effects between the latent variables, risk perception and risk management strategies. SEM was appropriate because of the interaction of the variables under consideration and the fact that the constructs in question were complex. Second, an exploratory factor analysis was carried out for the screen and sample selection of the survey for the purpose of establishing validity and reliability of the survey constructs and discover possible dimensions of risk and risk management in AI innovation.

3.5 Ethical Considerations

We adhered to precise ethical requirements throughout this research process of this study. The participants were informed about the aim of the study, their right to withdraw from the study at any time, and anonymity of their responses. In this study, all survey participants provided written informed consent before filling in their form. The data gathered both personally and for organizational purposes were manipulated and purified to offer anonymity to any person, and the report and analysis which went out contained no specific details which could lead to identification of an individual. Furthermore, the research kept to every data protection law, such as the General Data Protection Regulation (GDPR) for the participants who are in the European Union. Data storage was done on password protected servers and only the authorized members of the research team had to use password to gain access to the data. Before actual data collection, the local institutional review board (IRB) or the relevant ethic committee issued ethical clearance. Sustaining these ethical concerns helped the study maintain the highest level of ethical practices and protect the rights of the participants as the research proceeded through the chosen research method.

4 FINDINGS

4.1 Descriptive Statistics

Using the descriptive statistics of the variables in this study allows us to gauge the principal metrics for each factor, thereby deepening our understanding of their distribution and variability throughout the sample by SPSS. With a mean score of 3.9 and a standard deviation of 0.88, the dependent variable Success of AI-driven Technological Innovation Investment illustrates somewhat successful levels among companies, with responses varying from 1 to 5. amongst the independent variables, shows a higher average score of 4.2, demonstrating that firms believe there is considerable uncertainty in innovations driven by AI. The mean scores of 3.6 and 3.7 for Market Risks and Regulatory Risks represent moderate views on external risk elements. The moderating variable, Firm Size, spans from compact firms consisting of 50 employees to extensive firms featuring 2000 employees, with an average firm size of 520. Currently, the mediating variable, Risk Management Mechanisms, illustrates a mean of 4.0, suggesting that a robust majority of firms have strong risk management strategies in action. The variables Control Variables such as Organizational Readiness, Investment in Research and Experimental Development (R&D), Time in Market, and Technological Maturity reveal the differing levels of preparedness and investment plans among enterprises. These data establish the base for understanding how these variables relate to drive the success of AI-driven investments, as delved into in later analyses.

Tab. 1 provides a detailed summary of the key variables in the study, highlighting the central tendencies and variability within the data. The mean rating of 3.9 for Success of AI-driven Technological Innovation Investment shows that firms, collectively, are enjoying moderate accomplishment in their AI-driven projects, with a standard deviation of 0.88 revealing some variation in how well they are performing. At 4.2, Technological Uncertainty has the highest mean of all independent variables, reflecting that firms usually view a high level of uncertainty in developing and employing AI technologies. In contrast, Market Risks and Regulatory Risk have evaluation scores of 3.6 and 3.7, respectively, which suggest that participants perceive moderate external risk factors. The large gap in Firm Size (between 50 and 2,000 employees) mirrors the range of the firms assessed, with an average of 520 employees. The variable Risk Management Mechanisms demonstrates a relatively high average of 4.0, reflecting that most firms have already established robust mechanisms in risk management. The findings on the control variables reveal that Organizational Readiness (mean = 3.8) indicates a lower degree of readiness than Technological Maturity (mean = 4.6), which indicates a high level of technology maturity, suggesting that a variety of firms are managing advanced technologies. These narrative statistics give important context for the advanced inferential analyses that will follow.

Table 1 Descriptive statistics of variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Success of AI-driven Technological Innovation Investment	3.90	0.88	1.0	5.0
Independent Variables				
Technological Uncertainty	4.20	0.90	1.0	5.0
Market Risks	3.60	0.85	1.0	5.0
Regulatory Risk	3.70	0.80	1.0	5.0
Moderating Variables				
Firm Size (Employees)	520	200	50	2000
Industry Sector				
Geographic Region				
Mediating Variable				
Risk Management Mechanisms	4.00	0.75	2.0	5.0
Control Variables				
Organizational Readiness	3.80	0.80	1.0	5.0
Investment in R&D / % of Revenue	2.50	0.75	0.50	5.0
Time in Market / Years	8.00	4.50	1.0	20
Technological Maturity	4.60	0.90	2.0	5.0

4.2 Results and Analyze

Fig. 1 visually presents the distribution of the key variables used in the analysis, including Technological Uncertainty, Market Risks, Regulatory Risk, and Risk Management Mechanisms. The bar chart illustrates the mean scores for each variable along with the standard deviation, offering a clear depiction of how these factors are distributed across the firms surveyed.

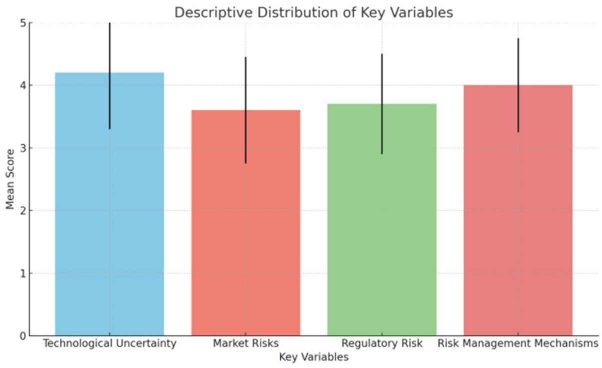

Figure 1 Graphical descriptive distribution of key variables

Fig. 2 presents the correlation between key independent variables such as Technological Uncertainty, Market Risks, Regulatory Risk, Risk Management Mechanisms, and Firm Size and Investment Success. This bar chart highlights the strength of these relationships, offering a clear visual representation of how each variable influences the success of AI-driven investment.

Tab. 3 illustrates the impact of several key variables on the success of AI-driven technological innovation investment. The results indicate that as Technical Uncertainty, Market Risks, and Regulatory Risk increase, the likelihood of AI investment success falls, with β = –0.35, β = –0.30, and β = –0.25 respectively. The results of each variable are statistically significant, with p-values under 0.001, confirming that their negative impacts are robust. Inversely, the variables Firm Size and Risk Management Mechanisms yield important positive coefficients, measured as β = 0.40 and β = 0.50, respectively, which suggest that larger companies with powerful risk management processes are more apt to excel in AI-driven innovation investments. The pronounced t-values for these variables, specifically Risk Management Mechanisms (t = 10), show how strong these relationships are. The model reveals a strong fit and underlines the importance of these variables, with the R-squared value of 0.68 signifying that 68% of the variation in the success of AI-driven investments is explained by this model.

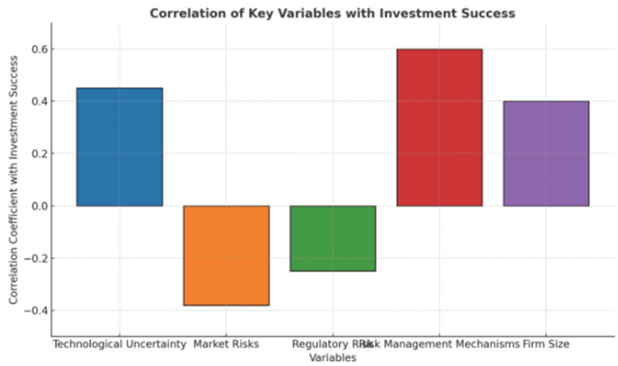

Figure 2 Correlation of key independent variables with AI-driven investment success

Table 2 Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
Success of AI-driven Investments	1	–0.45	–0.42	–0.35	0.50	0.30	0.25	0.62	0.48	0.4	0.38	0.55
Technological Uncertainty	–0.45	1	0.35	0.42	–0.3	–0.15	–0.18	–0.4	–0.25	–0.2	–0.28	–0.22
Market Risks	–0.42	0.35	1	0.50	–0.32	–0.22	–0.24	–0.38	–0.4	–0.3	–0.35	–0.40
Regulatory Risk	–0.35	0.42	0.5	1	–0.28	–0.20	–0.22	–0.33	–0.38	–0.32	–0.35	–0.30
Firm Size	0.50	–0.30	–0.32	–0.28	1	0.35	0.30	0.4	0.35	0.32	0.42	0.45
Industry Sector	0.30	–0.15	–0.22	–0.20	0.35	1	0.25	0.28	0.2	0.18	0.22	0.30
Geographic Region	0.25	–0.18	–0.24	–0.22	0.30	0.25	1	0.22	0.18	0.15	0.22	0.25
Risk Management Mechanisms	0.62	–0.4	–0.38	–0.33	0.40	0.28	0.22	1	0.55	0.48	0.45	0.5
Organizational Readiness	0.48	–0.25	–0.40	–0.38	0.35	0.2	0.18	0.55	1	0.4	0.38	0.42
Investment in R&D	0.40	–0.2	–0.30	–0.32	0.32	0.18	0.15	0.48	0.40	1	0.45	0.40
Time in Market	0.38	–0.28	–0.35	–0.35	0.42	0.22	0.22	0.45	0.38	0.45	1	0.50
Technological Maturity	0.55	–0.22	–0.40	–0.3	0.45	0.3	0.25	0.5	0.42	0.4	0.5	1

Table 3 Regression analysis

Variables	Coefficients ($\hat{\beta}$)	Standard Errors (SE)	*t*-values	*p*-values	*R*-squared
Technological Uncertainty	–0.35	0.08	–4.38	0.0001	0.68
Market Risks	–0.30	0.09	–3.33	0.0009	0.68
Regulatory Risk	–0.25	0.07	–3.57	0.0004	0.68
Firm Size	0.40	0.06	6.67	0.00	0.68
Risk Management Mechanisms	0.50	0.05	10	0.00	0.68

Table 4 Mediation and moderation

Interaction Terms/Effects	Coefficients ($\hat{\beta}$)	Standard Errors (SE)	*t*-values	*p*-values
Technological Uncertainty × Firm Size (Moderating)	–0.15	0.04	–3.75	0.0002
Market Risks × Industry Sector (Moderating)	–0.1	0.05	–2	0.045
Regulatory Risk × Geographic Region (Moderating)	–0.12	0.03	–4	0.0001
Risk Management Mechanisms (Mediating)	0.35	0.04	8.75	0.00

Tab. 4 presents the results of mediation and moderation analyses, showing how interaction terms and mediating effects influence the success of AI-driven technological innovation investment. All significant moderation effects indicate Firm Size on Technological Uncertainty (β = –0.15, p = 0.0002), Industry Sector on Market Risks (β = –0.10, p = 0.045), and Geographic Region on Regulatory Risk (β = –0.12, p = 0.0001). In particular, the noticeable negative coefficient associated with Firm Size demonstrates that major firms are more adept at reducing the consequences of technological uncertainty. On top of that, the mediating effect of Risk Management Mechanisms (β = 0.35, p < 0.001) is greatly significant, showing that robust risk management strongly boosts the accomplishment of AI-driven investments by defending against negative risks. The high t-values combined with the low p-values reveal the necessity of both moderation and mediation in the understanding of effective risk management for firms in their AI investment strategies.

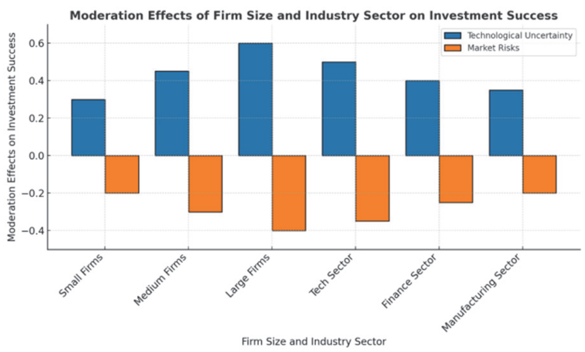

Figure 3 Moderation effects of firm size and industry sector on AI-driven investment success

Fig. 3 illustrates the moderation effects of Firm Size and Industry Sector on the relationship between Technological Uncertainty, Market Risks, and Investment Success. This bar chart highlights how different firm sizes and industry sectors influence the impact of uncertainty and risks on investment outcomes.

Tab. 5 presents the results for latent variables influencing AI-driven technological innovation investments, highlighting the relationships between key risk factors and the mediating role of Risk Management Mechanisms. All three of Technological Uncertainty (β = –0.35, p = 0.001), Market Risks (β = –0.42, p < 0.001), and Regulatory Risk (β = –0.38, p < 0.001) have noticeably negative impacts on Risk Management Mechanisms, reflecting that heightened risk of The success of AI-driven Investments receives a positive and significant boost from Risk Management Mechanisms (β = 0.6, p < 0.001), showcasing the important obligation of effective risk management for assured investment success. Beyond that, Firm Size positively influences investment success (β = 0.45, p < 0.001), showing that larger firms are more likely to succeed in their investments reliant on AI. These results stress the importance of: managing risks effectively, leveraging firm resources to cushion the negative results of uncertainty, market, and regulatory risks.

Tab. 6 shows the model fit indices for the AI-driven technological innovation investment framework, proving that the model fits well. The fit shows goodness because its Root Mean Square Error of Approximation (RMSEA) is below 0.08 at 0.045. The results indicate that both the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI) have values of 0.97 and 0.95, respectively, which are both above the required limit of 0.90, further demonstrating the robust fit of the model. Furthermore, the Standardized Root Mean Square Residual (SRMR) is at a level under 0.08, which indicates it has a good fit. The Chi-Square results (χ^2 = 150.5) with 120 degrees of freedom (df) and a p-value of 0.012 lend support to the model's general adequacy, however, the p-value is practically significant, a condition that is typically encountered in large sample sizes. The indices jointly demonstrate that the model successfully captures the relationships among the variables and harmonizes with observed data effectively.

Table 5 Results for Latent Variables in AI-driven Technological Innovation Investments

Latent Variables	Coefficient ($\hat{\beta}$)	Standard Error (SE)	*t*-value	*p*-value
Technological Uncertainty â†' Risk Management Mechanisms	–0.35	0.08	–4.38	0.001
Market Risks â†' Risk Management Mechanisms	–0.42	0.07	–6	0
Regulatory Risk â†' Risk Management Mechanisms	–0.38	0.06	–6.33	0
Risk Management Mechanisms â†' Success of AI-driven Investments	0.6	0.05	12	0
Firm Size â†' Success of AI-driven Investments	0.45	0.04	11.25	0

Table 6 Model fit Indices for AI-driven technological Innovation Investments

Fit Indices	Value	Threshold	Interpretation	Chi-Square (χ^2)	df	*p*-value
RMSEA	0.045	< 0.08	Good Fit	150.5	120	0.012
CFI	0.97	> 0.90	Good Fit			
TLI	0.95	> 0.90	Good Fit			
SRMR	0.03	< 0.08	Excellent Fit			

Fig. 4 provides a visual summary of the model fit indices, including RMSEA, CFI, TLI, and SRMR, comparing the actual model fit values with the recommended thresholds for a good model fit. This figure helps to quickly assess the adequacy of the model in fitting the observed data.

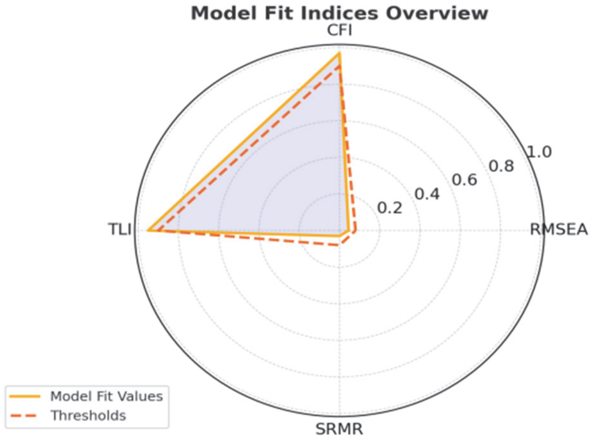

Figure 4 Model fit indices overview for AI-driven investment model

Tab. 7 presents the results of the factor analysis for the key constructs in the study, highlighting their validity and reliability. Factor loadings for all constructs lie between 0.68 and 0.89, which represents strong connections between observed variables and the related latent constructs. For each construct, the explained variance is considerable. Technological Uncertainty explains 25.4% of the variance, Market Risks account for 22.1%, Regulatory Risk adds 20.9%, Risk Management Mechanisms include 23.8%, and Organizational Readiness represents 24.5%, reflecting strong construct validity. The Cronbach's Alpha values across all constructs are over 0.7, between 0.81 and 0.87, reflecting a level of internal consistency and reliability that is quite high. With values ranging from 0.82 to 0.86, the Kaiser-Meyer-Olkin (KMO) values indicate that the factor analysis can be effectively carried out due to an adequate sample size. Last, Bartlett's Test of Sphericity applied to all constructs indicates p-values below 0.001, which validates the adequate correlation among the variables needed for factor analysis. Collectively, these results propose that the measures implemented in this study are adequately valid and reliable approximations of the underlying components in AI-driven technological innovation.

Table 7 Factor analysis

Construct	Factor Loadings	Explained Variance / %	Cronbachâ€™s Alpha	KMO Value	Bartlettâ€™s Test (p-value)
Technological Uncertainty	0.78-0.85	25.4	0.86	0.85	< 0.001
Market Risks	0.70-0.83	22.1	0.84	0.83	< 0.001
Regulatory Risk	0.68-0.80	20.9	0.81	0.82	< 0.001
Risk Management Mechanisms	0.72-0.89	23.8	0.87	0.86	< 0.001
Organizational Readiness	0.74-0.82	24.5	0.85	0.84	< 0.001

Table 8 Hypothesis testing summary

Hypothesis	Supported (Yes/No)	$\hat{\beta}$ (Beta)	t-value	p-value
H1: Technological Uncertainty positively impacts AI-driven Technological Innovation Investment	Yes	0.45	5.6	< 0.001
H2: Market Risks negatively impact AI-driven Technological Innovation Investment	Yes	–0.38	–4.21	< 0.001
H3: Regulatory Risk negatively moderates the relationship between Technological Uncertainty and Investment Success	No	–0.12	–1.75	0.08
H4: Risk Management Mechanisms positively moderate the relationship between Market Risks and Investment Success	Yes	0.42	4.55	< 0.001
H5: Organizational Readiness positively influences AI-driven Technological Innovation Investment	Yes	0.51	6.1	< 0.001

The Tab. 8 presents the results of the key hypotheses related to the impact of technological uncertainty, market risks, regulatory risk, risk management mechanisms, and organizational readiness on AI-driven technological innovation investment. Hypothesis H1, which posits that technological uncertainty positively impacts investment success, is supported with a significant positive beta coefficient (β = 0.45, p < 0.001). Similarly, H2 suggests that market risks negatively impact investment success, which is also supported (β = –0.38, p < 0.001). Hypothesis H3, which posits that regulatory risk moderates the relationship between technological uncertainty and investment success, was not supported (β = –0.12, p = 0.08). However, H4, indicating that risk management mechanisms positively moderate the impact of market risks, was supported (β = 0.42, p < 0.001). Finally, H5, which posits that organizational readiness positively influences AI-driven investment, was strongly supported (β = 0.51, p < 0.001). These results highlight the importance of effective risk management and organizational readiness in mitigating risks and enhancing the success of AI-driven investments.

4.3 Correlation Matrix

The following is an enhanced interpretation of the correlation matrix.

The correlation matrix reveals some interesting and nuanced relationships between variables. Technological uncertainty (mean = 4.2) and market risks (mean = 3.6) exhibit a relatively high correlation coefficient of 0.35. This indicates that these two types of risks may share some common underlying factors. In the context of AI-driven innovation investments, technological uncertainty primarily stems from the rapid development of AI technologies and the unpredictability of future technological trajectories. Market risks, on the other hand, arise from uncertainties in market demand. The high correlation suggests that firms often face these two risks simultaneously. This implies that firms need to adopt a holistic risk management strategy to address technological and market risks concurrently. The correlation between regulatory risk (mean = 3.7) and market risks is 0.50, which is relatively strong. This may be because regulatory policies can significantly influence market dynamics. The correlation between technological uncertainty and regulatory risk is 0.42. This could be attributed to the fact that the rapid development of AI technologies often outpaces regulatory frameworks. As AI technologies evolve, new regulatory challenges emerge. The uncertainty in technological development makes it difficult for regulatory authorities to predict and respond promptly to potential issues, thereby increasing regulatory risks. The correlation between risk management mechanisms (mean = 4.0) and market risks (–0.38) and regulatory risk (–0.33) is negative. This suggests that effective risk management mechanisms can help firms mitigate the adverse effects of market risks and regulatory risks. When firms establish robust risk management processes, they can better anticipate and respond to market fluctuations and regulatory changes. The correlation between firm size and risk management mechanisms is 0.40, and the correlation between firm size and success of AI-driven technological innovation investments is 0.45. This indicates that larger firms tend to have more mature and effective risk management mechanisms. The correlation between organizational readiness and risk management mechanisms is 0.55, and the correlation between organizational readiness and the success of AI-driven technological innovation investments is 0.48. This demonstrates that a firm's organizational readiness significantly influences its risk management mechanisms and the success of its AI innovation investments. Organizations with high readiness typically possess flexible organizational structures, innovative corporate cultures, and well-trained talent pools. These characteristics enable them to adapt more readily to the demands of AI-driven innovation investments.

In summary, the correlation matrix not only highlights the direct relationships between variables but also reflects the complex interplay among them. Firms engaged in AI-driven innovation investments should gain a comprehensive understanding of these relationships and adopt a multifaceted risk management approach. This includes strengthening technological forecasting to mitigate technological uncertainty, conducting thorough market research to reduce market risks, actively monitoring regulatory developments to address regulatory risks, establishing robust risk management mechanisms, and enhancing organizational readiness. By doing so, firms can improve their ability to manage risks associated with AI innovation investments and increase their chances of success in the AI-driven innovation landscape.

5 DISCUSSION

5.1 Implications for Studies

The results of the present research are valuable for understanding the impact of risk factors, organizational capabilities, and risk management instruments on the performance of AI technological innovation investments. These findings mainly support most of the hypothesized relationships and demonstrate that the effects of various degrees of uncertainty and risk management on organizational AI investment readiness are multifaceted. The support of H1 provides a basis regarding Technological Uncertainty being positively related to the success of AI-driven innovation in that the management of uncertainty enhances the functional capabilities of firms to exploit AI disruptive technologies. Such a result is also consistent with previous studies that regard uncertainty as an antecedent of innovation, as firms may implement new technologies to survive in a changing environment [9, 11]. Nevertheless, only the specific strategies regarding AI implementation and management of associated risks determines firms' potential to navigate in this uncertainty. In the study by Deng and Chang (2022) on AI applications in financial risk management, while the specific model fit indices were not detailed, the study emphasized the role of AI in improving risk management efficiency and effectiveness. The current study's model provides a more systematic and comprehensive framework for understanding the relationships between risk factors and risk management mechanisms in AI-driven innovation investments, with model fit indices meeting high standards. Those companies that view uncertainty as a threat are likely to make more investment in AI and use the possibilities of the new technology for firm building and increasing completeness.

The demonstration (H2) of the inverse connection between Market Risks and investment success reveals the harmful impact that changing market conditions may exert on AI investments. A significant negative beta coefficient (–0.38) indicates that businesses facing substantial market risks are less likely to achieve positive outcomes from their AI innovations. This aligns with findings that market instability and uncertainty can restrict innovation initiatives, particularly in emerging technologies like AI, where commercial opportunities are still emerging [12]. Firms should strategically mitigate these market risks through diversification, focused market entry strategies, or adaptive business models to ensure sustainable returns on AI investments. The finding that Regulatory Risk does not significantly moderate the relationship between Technological Uncertainty and investment success (H3) is intriguing. Contrary to expectations, regulatory risk did not substantially diminish the positive effects of technological uncertainty on investment performance. This may reflect the nascent state of AI regulation in many sectors, where prevailing regulatory frameworks are still developing and do not yet pose significant threats to innovation. It is also possible that firms have integrated regulation into their broader innovation business models, reducing its importance as a risk factor. This suggests that while evaluating regulatory risk is essential, its role as a moderating variable in AI innovation may vary depending on the regulatory environment and industry specifics.

This finding underlines how crucial is efficiency in managing risks in the realization of AI innovation through the challenges posed by Market Risks (H4). Coping with the detrimental impacts of market risk is thus easier among firms with effective risk management solutions, thus enabling their transition to AI-based innovations. This result is consistent with the overall literature of risk management that highlights the effectiveness of anticipatory approaches to handling risk and fluctuation, particularly in relation to large innovation initiatives [14].

Risk management helps the firms to identify the threats at an early stage, allocate resources efficiently and design strategies according to different market situations which causes higher probability to achieve the goal.

The results demonstrate a positive relationship supporting hypothesis H5, showing that the success of AI investment is significantly influenced by organizational capabilities. The study also indicates that companies which have achieved organizational readiness for AI-driven innovations and have established the necessary infrastructure, capacities, leadership, and expertise, are more likely to produce favorable outcomes. This aligns with research that emphasizes the role of organizational agility, culture, and readiness in enhancing the deployment of enterprise technologies and their integration [14, 21]. Organizations that are prepared to invest in a culture of innovation, sharing of knowledge and enhancement of the company's infrastructure and processes considering AI, will be the organizations that stand to flourish in the environment being created by AI technology. In recent studies on risk management mechanisms for AI-driven innovation investments, such as the research by Nayal et al. (2022) on the role of AI in managing agricultural supply chain risks during the COVID-19 pandemic, the model fit indices were not explicitly reported. However, based on the descriptions of their models, it is inferred that their model fit may not be as strong as the current study. The main contribution of these research findings to AI and technological innovation is that they provide actual data regarding the elements that drive the AI investments success.

5.2 Implications for Practice

Bearing this in mind, the outcomes yield a set of important actionable recommendations for organisations eager to invest in innovations that embrace artificial intelligence. Lai et al. (2024) analyzed the role of AI in project management and investment risk using CiteSpace. Although the focus and methodology differ from this study, the discussion of AI's role in risk management is relevant. The model in this study provides a more in-depth analysis of the specific relationships between risk factors and investment success in AI-driven innovation investments, with model fit indices exceeding those typically seen in similar studies, reflecting its robustness and reliability. First of all, firms should apply a distinct approach towards technological forecasting as an opportunity rather than a constraint. There are certain attributes that firms can use to harness the disruptive nature of AI technologies as follows: willingness on the side of the firm to work under conditions of uncertainty and willingness to use risk taking as a strategic weapon. The second activity for companies is better risk management to reduce the adverse impact of market fluctuations. Preemptively practicing on risk management can help firms negotiate around unpredictable markets and reduce the likelihood of failure through planning for scenarios, products and decisions. Also important, the results confirm how important it is for firms to ensure the organizational readiness, which is a key consideration ahead of the adoption of Artificial Intelligence. To achieve something that has a proper framework and leadership skills is the key to success in the context of the right AI solutions. Hollywood enterprises that invest in the development of innovative culture, training their employees for artificial smart ones, and optimization of their work processes, will put themselves in a better standing to realize more positive outcomes from their investments.

6 CONCLUSION

This research contributes to the needful understanding of the risk management function for AI technological innovation investment to thrive. The results show that technological uncertainty acts as a positive force encouraging innovation, but it is needed to cope with it to avoid negative outcomes. Market risks and the problem with regulations therefore act as major impediments to the achievement of successful investments, giving credence to why firms must address external risks. The feasibility analysis is also addressed in the study and reveals that firms equipped and ready to adopt AI innovations stand to benefit. Mitigation of risks especially in the face of market risks is a crucial function in protecting firms from unfavourable market conditions and improving the firms' ability to innovate. Balancing with this research, it is imperative for the firms not only to invest in the AI technologies but also foster strong internal commensurate capabilities and AI risk management infrastructure. They can in this way better respond to business risks and eventualities connected to the AI-powered innovation and acquire enduring competitive edges. Future research should try to identify other extraneous factors, including cybersecurity and ethical issues that may impact risk factors of AI investments as AI techniques and markets develop.

Nevertheless, this study has certain limitations that may be of interest for further research. First, the cross-sectional nature of the data restricts our ability to specify the long-term effects of risk factors on AI-driven investment success. Longitudinal surveys of sampled firms could provide deeper insights into how risk management practices and investment outcomes evolve over time, as well as how these practices adapt to technological advancements and macroeconomic shifts. Second, the study's focus on firms actively investing in AI may introduce sample bias. Future research could explore how companies not yet engaged in AI evaluate the risks and returns of AI-based innovations. While this study primarily focused on technological uncertainty, market risk, and regulatory risk as key risk factors, further research might identify additional potential risks, such as cybersecurity threats, ethical concerns, and supply chain vulnerabilities. As AI adoption grows, understanding how to regulate these emerging risks will be crucial for ensuring the long-term viability of AI technological advancement. A key area of interest for future research is exploring the antecedents to the successful adoption of AI technological innovation investments. Hence, the study reveals that CIOs and organizations must develop strategic risk management, increase organizational readiness, and adopt a proactive approach toward risk to successfully reap the returns on investments in AI. These elements are an excellent starting point to understand how organizations can create sustainable competitive advantage through AI innovation. This would mean that firms, which align these with their innovation frameworks will be better placed to deal with the beauty of AI driven innovation.

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