

AI Utilization and Governance in Corporate Entrepreneurship: Investigating the Moderating Influence of Top Management

Chuyi Fang ¹
Hanyun Li ¹
Yuting Wang ^{1,*}

*Corresponding author

¹ Shanghai University, Shanghai, China, chuyifang@shu.edu.cn

¹ Shanghai University, Shanghai, China, 815310068@qq.com

¹ Shanghai University, Shanghai, China, yutingw@shu.edu.cn

ABSTRACT

Given the limited understanding of AI's impact on corporate entrepreneurship, this study explores how AI resources (AI utilization and AI governance) promote corporate entrepreneurship, especially with top management's involvement. Using data from Chinese firms and hierarchical regression analysis, findings reveal that AI utilization and governance positively impact corporate entrepreneurship. Top management beliefs positively moderate the impact of AI utilization and AI governance on corporate entrepreneurship. Top management participation negatively moderates the effects of AI utilization and AI governance on corporate entrepreneurship, with no significant moderating effect of AI governance on corporate entrepreneurship. The findings suggest that managers better maintain a positive attitude toward AI technology and gain in-depth knowledge in AI-related concepts to promote corporate entrepreneurship.

Keywords: AI utilization, AI governance, corporate entrepreneurship, top management beliefs, top management participation.

INTRODUCTION

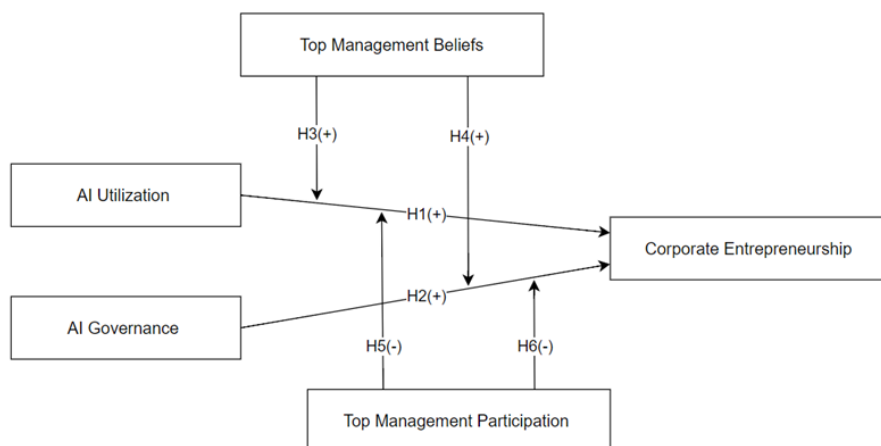
With the rapidly shifting dynamics of the global market and the development of technology, firms are encountering intense competitive challenges and rapid technological advancements. Corporate entrepreneurship (CE) has gained widespread recognition in this dynamic business environment as a crucial approach for firms to achieve sustainable competitive advantage and foster innovation (Tootoonchy & Sajadi, 2024). CE promotes an entrepreneurial mindset. It helps businesses innovate and prepare for market challenges and opportunities (Niemann et al., 2022). Over the last few decades, CE has made notable advancements in practice. Certain firms proactively seek external innovation resources and collaborate or acquire start-ups to expedite innovation and market-oriented development. For example, through significant R&D investments, Samsung developed the Galaxy series of smartphones, exceeding consumer expectations and becoming a global leader (Mosavi & Kenarehfar, 2013). This commitment to CE allowed Samsung to adapt to market trends, anticipate needs, and drive product innovation, ensuring long-term success in a competitive industry. Despite its potential benefits, CE encounters challenges and obstacles in practice. One challenge is the limitation of resources and budgets, restricting firm activities and investments in CE. Consequently, striking a balance between innovation and risk, along with optimizing resource allocation, becomes a critical consideration for firms embarking on CE implementation.

Recent advancements in artificial intelligence (AI) present opportunities to promote successful CE in firms. By harnessing the potential of AI and leveraging its analytical capabilities, firms can enhance their decision-making processes, allocate resources more effectively, and mitigate risks associated with CE implementation (Davidsson & Sufyan, 2023). Given the rapidly evolving business environment, studying the impact of AI on CE is very important. The effective utilization and governance of AI in firms can facilitate the realization of CE. On the one hand, using resources such as automation and intelligent applications has presented numerous business opportunities for firms, igniting creativity and highlighting novel business paradigms. On the other hand, in the absence of management of allocation and use of resources, AI has resulted in the wastage of valuable assets, misuse of data, and unfair situations. Insufficient governance and ethical constraints on AI can further impede firms' innovative entrepreneurial activities. Resource-based view (RBV) theory emphasizes the significance of how firms acquire and allocate resources (Zahra, 2021). As a crucial resource and technology, AI profoundly affects entrepreneurial activities. However, limited research has focused on distinguishing AI's heterogeneous role in value creation. Therefore, this study focuses on two crucial utilization methods of AI resources in the firms (AI utilization and AI governance) and their impact on CE, thus contributing to existing theories. We perceive AI utilization as harnessing AI technologies for future trend prediction, statistical analysis, and supply chain decision-making in response to environmental changes. AI governance is regarded as policies and practices firms have established for AI's responsible and ethical management (Rana et al., 2022).

The value of AI is contingent upon the level of support it receives from top managers. Without adequate commitment and involvement from top-level management, AI's potential benefits may remain unrealized or underused. This underlines the

significance of top management's role as a driving force and a crucial moderating factor in the relationship between AI and CE. To shed light on this moderating role, we delve into the perspectives of top management beliefs (TMB) and top management participation (TMP), which collectively capture the attitudes and active involvement of senior executives in AI-related initiatives. TMB and TMP's influence can be considered a pivotal mechanism by which AI shapes CE within the firm. It is widely recognized that top executives' strategic decisions and directional guidance pave the way for firms, ensuring that their efforts align with overarching goals (Tekic & Koroteev, 2019). Nonetheless, it is important to note that digital transformation, in which AI plays a central role, demands more than visionary leadership; it necessitates effective management practices, encompassing skill development, change management, and fostering organizational agility. Therefore, firms that proactively adjust their structures and processes to accommodate the integration of AI may encounter challenges as they strive to realize AI's potential benefits for entrepreneurial activities fully. These challenges bring the moderating influence of TMB and TMP into sharp focus, as they significantly impact the extent to which AI-driven CE can be achieved and sustained within the firm.

Within the context of AI development, our research focuses on two main issues: we first investigate the impact of AI utilization and governance on CE. Further, we delve into the moderating role of TMB and TMP in the relationship among AI utilization, AI governance, and CE. This paper makes the following contributions to the study of CE. Previous literature has mainly focused on examining the impact of big data management and IT governance on corporate innovation (Wang et al., 2015), and explored how to make use of IT capabilities to gain competitive benefits (Mai et al., 2024). For example, exploring how IT affects a firm's opportunity exploration capabilities demonstrates the importance of IT, while also providing significant insights for firms to gain strategic advantages (Benitez et al., 2018). However, traditional IT, such as information systems and data management, mainly focuses on data storage, processing, and transmission. In contrast, AI possesses higher complexity and intelligence levels. It can provide value to entrepreneurial activities through automated decision-making and prediction via deep learning. Nonetheless, the use of AI relies on human training. Therefore, the emerging role of AI in CE warrants further exploration. We go a step further by considering AI utilization and governance as two critical AI in management, studying their impact on CE and expanding the mechanism of how AI influences CE. Second, current research mainly provides a broad discussion on the moderating role of top management teams (TM teams) (Pan et al., 2021), suggesting that TMT can lead the emergence of innovation. Since innovation is only a part of CE, this paper narrows the focus to the specific impact of top management on CE. We argue that different attitudes and levels of involvement of top management towards AI can result in varying effects of AI on CE. Specifically, we delve deeper into the distinct moderating effects of TMB and TMP on the impact of AI on CE. Figure 1 describes the research model we propose.



Source: This study.
Figure 1: Research model.

THEORETICAL BACKGROUND AND LITERATURE REVIEW

RBV Theory

RBV theory, a prominent and widely referenced framework in management, posits that a firm's effectiveness and organizational performance are primarily influenced by its internal resources (Kassa & Tsigu, 2022). The theory asserts that firms can secure sustained competitive advantages by effectively leveraging their internal resources. It posits that resources are heterogeneously distributed across firms and that to provide competitive advantages, organizational resources must exhibit four characteristics: they must be valuable, rare, imperfectly imitable, and non-substitutable (Barney, 2016). The development of a firm is based on the available set of organizational resources. Therefore, the strength of a firm's development depends on the resources it relies on for growth (Mikalef & Gupta, 2021).

As a resource, AI enables firms to access unique insights and decision support, distinguishing them in competitive markets (Kemp, 2024). Due to its scarcity and difficulty in replicating, AI is a valuable asset for enhancing corporate entrepreneurship. It supports large-scale data processing, task automation, intelligent analysis, and predictive capabilities. By leveraging the resources generated through AI technologies, firms can achieve superior competitive performance in marketing (Rahman et al., 2021). By using AI, firms can better organize and manage their internal resources, improving production efficiency and quality.

Although AI technology itself may be universally available, the data assets possessed by different firms are unique. This makes the effectiveness of AI utilization by each firm irreplaceable. Additionally, AI governance within firms differs, creating unique, differentiated development that facilitates effective decision-making, which is difficult to replicate.

Since the purpose of this study is for firms to use existing AI resources to promote CE, the RBV theory provides a useful framework for understanding how AI impacts CE. Through the lens of RBV, we can theorize the strategic importance of organizational resources. Additionally, we can establish the relationship between AI resources as an independent variable and CE as a dependent variable. Furthermore, AI governance aids in ensuring alignment between AI and the firm's strategic goals and vision. This strategic coordination helps ensure that the application of AI technology is in harmony with the success of entrepreneurial activities.

Artificial Intelligence (AI)

AI can be defined as a system's ability to learn accurately from external data and apply the acquired knowledge to achieve specific goals and tasks (Haenlein & Kaplan, 2019). Given that AI represents a further development within the realm of IT, AI utilization and AI governance are categorized as primary AI resources, similar to IT assets and IT management, in line with Wang et al. (2015). AI utilization refers to firms' use of AI technologies and algorithms for data processing, decision-making, automation, and insight generation (Belhadi et al., 2021). AI offers the opportunity to help companies discover new approaches that can be applied to business strategy. For instance, Amazon utilizes AI algorithms to analyze customer behaviors, such as past purchases and browsing history, to provide personalized product recommendations and targeted marketing campaigns. Meanwhile, AI governance establishes frameworks, policies, and practices for AI's responsible and ethical management within firms (Winter & Davidson, 2019); (Rana et al., 2022). This framework encompasses assessing and regulating AI algorithms, data, and decisions to ensure that AI deployments comply with ethical guidelines and requirements. For example, Google's AI governance is a set of guidelines. This practice guarantees accurate and impartial search results, demonstrating Google's commitment to ethical standards and compliance.

AI utilization is critical to the growth of entrepreneurial activities. Our research on AI utilization delves into how firms leverage AI for statistical analysis, trend forecasting, and decision support across various levels. At the same time, effective AI governance is crucial for firms to ensure AI's responsible and ethical use to promote entrepreneurial activities (Winter & Davidson, 2019). Ensuring AI applications adhere to ethical and regulatory requirements mitigates potential risks, cultivating an environment conducive to ongoing entrepreneurial activities.

Corporate Entrepreneurship (CE)

As a tool for strategic renewal and change, CE enables firms to embrace innovation and an entrepreneurial mindset. We define CE as the combination of innovative processes for introducing products, production processes, and organizational systems, as well as changes to the firm's business scope and competitive approach to promote the firm's strategic renewal (Zahra, 2021). CE plays a crucial role in propelling firm growth, fostering an environment conducive to continuous innovation, and the introduction of novel products or services. This, in turn, boosts market competitiveness and profitability, making CE an indispensable factor for firm development (Usai et al., 2021).

Some researchers have studied the factors affecting CE to understand better how to maximize its positive effects. Since CE involves innovation and strategic renewal, studies have focused on how firms use IT to promote product and service innovation (Orozco et al., 2022). Other research has examined how technological development and management support for technology can drive corporate innovation, highlighting the contribution of management and organizational mechanisms to CE. With the advancement of technology, innovative firms not only focus on the role of IT in entrepreneurship but also pay more attention to using emerging AI technologies to drive corporate innovation (Rammer et al., 2022). Firms benefit from the spillover effects of innovative development in the information and communications technology (ICT) sector, and the technological advantages of top AI innovators have also increased.

Top Management Beliefs (TMB) and Top Management Participation (TMP)

Effective intervention by top management can improve the entrepreneurial ability of the firm. According to Gopalakrishna-Remani et al. (2019), top management can be classified into TMB and TMP. TMB refers to the psychological state of top managers regarding the potential value of their strategic choices, whereas TMP refers to the actions and activities top management takes to facilitate the implementation of strategic choices (Liang et al., 2007). In this paper, TMB refers to the executives' willingness to proactively establish goals and criteria for overseeing the implementation of AI to enhance business processes, structures, and models. Meanwhile, TMP signifies top management's personal engagement and active involvement in integrating AI technologies within the firm. TMB and TMP are integral components of the top management team (TMT), which has a universal structure and guides the firm's future development. TMT plays a crucial role in understanding internal complexity during strategic decision-making, thus promoting strategic change and innovation (Yang & Wang, 2014). As firms increasingly invest in AI to facilitate knowledge exchange and employee innovation, top management's effective use of digital knowledge becomes vital for accelerating digital innovation.

DEVELOPMENT OF HYPOTHESES

The Impact of AI on CE

According to RBV theory, AI technology, as a new type of resource, has gradually impacted firms. On the one hand, increased AI utilization allows firms to forecast trends, perform statistical analyses, and provide decision-making information. Several studies have demonstrated that AI technology provides more accurate market insights and customer service analytics. This can result in more effective use of resources and potentially more successful and innovative products, enhancing the firm's ability to introduce many new products to the market (Verganti et al., 2020). On the other hand, increasing AI utilization aids firms in uncovering novel business opportunities and market demands. AI technology can process and analyze extensive data, revealing market development trends submerged in vast information. Consequently, firms can obtain inspiration and innovative directions from AI for more forward-looking and sustainable development.

Moreover, enhancing AI utilization improves firms' decision-making efficiency, thereby fostering CE. AI can improve the methods and efficiency of internal collaboration and information sharing in firms, breaking down traditional departmental barriers and information silos. Through AI implementation, firms can acquire comprehensive information from massive datasets and make more astute decisions based on this wealth of knowledge. This precise and personalized decision support aids firms in avoiding impulsive actions during entrepreneurial activities. Simultaneously, firms can better coordinate internal and external resources and take appropriate measures to meet ever-evolving market demands. These not only change their competitive approach but also enhance their entrepreneurial ability. Therefore, we hypothesize the following:

Hypothesis 1: AI utilization has a significant positive effect on CE.

AI governance can provide support and assurance for CE. According to the RBV theory, a unified standard of unique and valuable resources is crucial for achieving outstanding performance and long-term success in a competitive business environment. Robust AI governance ensures ethical use and transparency in AI systems. This builds solid relationships among employees, customers, and stakeholders, which is crucial for a culture encouraging innovation (Winter & Davidson, 2019). If firms manage their AI carefully to ensure that they align with their strategic goals and purposes, this can further promote innovative development (Sjödin et al., 2021). Moreover, effective AI governance includes standards for data quality and model reliability. This ensures the use of high-quality data, leading to successful entrepreneurial ventures and sparking innovative products, services, and business models (Paschen et al., 2019). Establishing a robust AI governance framework provides firms with essential guidelines and rules to mitigate entrepreneurial risks. Robust AI governance with reduced bias, increased transparency, and a deeper comprehension of AI decision-making processes bolsters the pursuit of innovative opportunities with the assurance that the underlying technology is both reliable and compliant. Therefore, strengthening AI governance can assist firms in conducting business analysis, providing better conditions and guarantees for CE. To explore the relationship between corporate AI governance and CE, our next hypothesis is as follows:

Hypothesis 2: AI governance has a significant positive effect on CE.

Moderating Role of TMB

In the digital transformation era, top-level executives universally recognize the potential of adopting AI technology to benefit their firms significantly. If top executives believe in the value of AI and encourage employees to take risks and try AI technologies, this can lead to the development of new products, services, and business models and give the firm a competitive advantage (Choi et al., 2021). Moreover, top executives engage in strategic decision-making, identify new investment opportunities, and expand the firm's business scope by supporting AI utilization. When top-level executives believe that AI utilization can bring more business opportunities and enhance the firm's competitive advantage, they will likely be more proactive in driving AI's adoption to foster entrepreneurial activities. TMB can foster the more proactive adoption of AI for statistical analysis and decision-making, fostering innovation in organizational structures and entrepreneurial activities.

If top executives believe in fully utilizing AI technology and grasp its potential and advantages, they may be more proactive in formulating and implementing corresponding AI governance strategies to promote digital transformation and enhance corporate efficiency and competitiveness. Furthermore, if top executives are aware that AI technology is not a panacea, they may use AI technology more cautiously to avoid possible risks and losses. This caution is also a part of CE. Top executives recognize that implementing AI technology requires an effective governance framework, which will help ensure that the firm complies with ethical norms and regulations in using AI technology while reducing conflicts with employees, customers, or other stakeholders. Doing this will maintain the firm's reputation while enhancing the sustainability of its CE. Thus, we hypothesize the following:

Hypothesis 3: TMB plays a positive moderating role in the impact of AI utilization on CE.

Hypothesis 4: TMB plays a positive moderating role in the impact of AI governance on CE.

Moderating Role of TMP

TMP emphasizes the active participation of top managers in formulating strategies to promote the utilization and governance of AI during the digital transformation process, thereby driving entrepreneurial activities within the firm. By actively involving managers and senior leaders in using AI technology, TMP strives to create a culture of innovation that permeates the entire firm (Yu et al., 2022). When top-level leaders are intricately involved in the technology innovation process, they can provide valuable

guidance and direction to help steer innovation plans toward areas with the greatest long-term impact on the firm's success. Firms that integrate top-level personnel in digital management can better achieve long-term success and uphold a competitive edge.

Some firms may adopt management practices with negative implications, where executive leadership disregards or overlooks AI technology's potential risks and threats. Conversely, excessive intervention and control by top management over AI may impede innovation and exploration. By imposing strict regulations and restrictions, top executives may limit employees' freedom to create and explore AI technology, thereby hindering the motivation and innovation capacity of CE. AI is an iterative process that requires continuous learning, and top-level management must appreciate the significance of training AI with specific professional knowledge to achieve the desired outcomes. Despite top-level executives' active implementation of digital transformation or AI strategies, errors could arise due to their unfamiliarity with the technology. Therefore, we hypothesize the following:

Hypothesis 5: TMP plays a negative moderating role in the impact of AI utilization on CE.

Hypothesis 6: TMP plays a negative moderating role in the impact of AI governance on CE.

METHOD

Sample and Procedures

To test the hypotheses, we collaborated with a media firm responsible for disclosing information about listed firms. The firm collaborated with us by inviting customers to participate in the survey to obtain data. Initially, we obtained a list of 200 listed firms (i.e., customers of the media firm), representing various industries such as manufacturing, information technology services, finance, and wholesale. The top executives of these firms are our responders. Table 1 reveals the proportion of male respondents. They were informed that an academic institution conducted this study solely for academic purposes and that the results would not be used for commercial purposes. Questionnaires detailing the study's purpose, content, and requirements were distributed to the participants. After discarding incomplete questionnaires, 149 (out of 200) were obtained, with a response rate of 74.5%. Because of the incompleteness of some data, we eliminated 36 questionnaires, leaving us with 113.

To examine the non-response bias, we conducted a t-test to compare key characteristics between the first 25% and the last 25% of respondents (Armstrong & Overton, 1977). The results indicate no significant differences in AI utilization ($t = -0.612$, $p = 0.543$), AI governance ($t = 0.832$, $p = 0.409$), and CE ($t = -1.477$, $p = 0.145$) between these two groups. Thus, non-response bias does not appear to be a significant issue in our sample.

Table 1: Demographic information.

	Frequency	Percent (%)
Respondent gender		
Male	74	65.5
Female	39	34.5
Respondent age		
21–30 years old	2	1.8
31–40 years old	6	5.3
41–50 years old	57	50.4
51–60 years old	44	38.9
Over 60 years old	4	3.6
Respondent education level		
Associate degree	6	5.3
Bachelor's degree	54	47.8
Master's degree	50	44.2
Doctoral degree	3	2.7

Source: This study.

Measures

The survey was initially developed in English using measures validated in the existing literature. All items were measured using a Likert five-point scale, with 1 representing "strongly disagree," 2 representing "disagree," 3 representing "neutral," 4 representing "agree," and 5 representing "strongly agree". Because this study was conducted in China, the English survey was translated into Chinese following the procedure Van de Vijver & Leung (2021) recommended. The translated survey was then sent to scholars and practitioners to check for comprehension and accuracy. Following some adjustments, a proficient translator without prior knowledge of the research project translated the Chinese survey into English. The back-translated survey was compared to the original, and no significant semantic differences were found between the two versions.

According to Belhadi et al. (2021), the degree of AI utilization was determined. Four items were used to design the questionnaire. Following the design of AI governance in Rana et al. (2022) questionnaire. TMB and TMP were measured using two and three items, respectively (Gopalakrishna-Remani et al., 2019). CE, we adopted the approach Zahra (1996) proposed and used six items to assess the evaluation of a firm's commitment to innovation, venturing activities, and strategic renewal. See Appendix A for all items. Additionally, respondent gender, age, education level, and position were considered individual-level control variables that affected CE. These control variables were measured using dummy variables. Firm age and size were regarded as firm-level control variables affecting CE. The size of a business was measured by the number of employees.

RESULTS

Measure Validation

We evaluated the validity and reliability of the measurement model using SPSS 24.0. As Table 2 shows, all constructs' average variance extracted (AVE) scores exceeded the benchmark value of 0.500. The estimated Cronbach's alpha and composite reliability values were higher than the benchmark value of 0.700, indicating that the measurement model had good convergent validity and reliability. Further, the factor loading of all the items was also greater than 0.70, which is in line with Fornell & Larcker (1981), indicating that the correlations among the constructs were lower than the corresponding square root of the AVE scores. Therefore, the dataset exhibited good discriminant validity.

Table 2: Cronbach's alpha, composite reliability, AVE, and loading of indication variables.

	Items	Loading	Cronbach's alpha	Composite reliability	AVE
AIU	4	0.898~0.927	0.936	0.954	0.841
AIG	3	0.719~0.913	0.805	0.887	0.725
TMB	2	0.957	0.907	0.956	0.916
TMP	3	0.915~0.949	0.925	0.952	0.870
CE	6	0.725~0.834	0.873	0.905	0.614

Source: This study.

Note: AIU: AI utilization; AIG: AI governance; TMB: Top management beliefs; TMP: Top management participation; CE: Corporate entrepreneurship.

Moreover, Table 3 provides a comprehensive overview of the construct correlations and the square roots of AVE scores. It illustrates the relationships between different constructs in our analysis. The results show that the correlations among the constructs were lower than the corresponding square root of the AVE scores.

Table 3: Means, standard deviations, and correlations.

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
AIU	3.331	1.086	0.917	0.052	0.210*	0.472**	0.597**	-0.222*	-0.09	-0.052	0.226*	-0.016	0.038	0.180*
AIG	2.560	0.939	-0.034	0.851	-0.270*	-0.024	0.067	-0.188*	0.004	-0.054	-0.236*	0.079	-0.152	-0.373**
TMB	4.146	0.664	0.223*	-0.248*	0.957	0.626**	0.236**	0.150	-0.023	-0.010	0.108	-0.110	0.061	0.260**
TMP	3.791	0.783	0.481**	0.007	0.632**	0.933	0.503**	-0.010	0.032	0.000	0.141	-0.100	0.085	0.295**
CE	3.481	0.831	0.604**	0.083	0.249**	0.511**	0.784	0.064	-0.050	-0.078	0.214*	-0.100	-0.027	0.202*
GEN	N.A.	N.A.	-0.201*	-0.168	0.164	0.007	0.080	N.A.	-0.139	-0.064	0.052	-0.093	0.074	0.042
AGE	N.A.	N.A.	-0.071	0.021	-0.006	0.048	-0.032	-0.120	N.A.	0.024	-0.076	-0.159	0.108	-0.053
CUL	N.A.	N.A.	-0.034	-0.036	0.007	0.017	-0.606	-0.046	0.041	N.A.	0.082	-0.009	0.076	-0.102
EXE	N.A.	N.A.	0.239**	-0.215*	0.123	0.156	0.227*	0.068	-0.058	0.098	N.A.	0.052	0.145	0.000
SCALE	18821.31	5097.665	0.001	0.095	-0.091	-0.081	-0.081	-0.074	-0.139	0.008	0.068	N.A.	0.119	-0.054
EAGE	23.354	7.032	0.054	-0.132	0.077	0.101	-0.010	0.090	0.123	0.092	0.160	0.134	N.A.	0.002
MV	N.A.	N.A.	0.194*	-0.35**	0.273**	0.307**	0.216*	0.058	-0.035	-0.083	0.017	-0.036	0.019	N.A.

Source: This study.

Note:

1. The diagonal elements are the square roots of AVEs. Unadjusted correlations appear below the diagonal; correlations adjusted for the common method appear above the diagonal. * shows significance at the 0.05 level; ** shows significance at the 0.01 level.

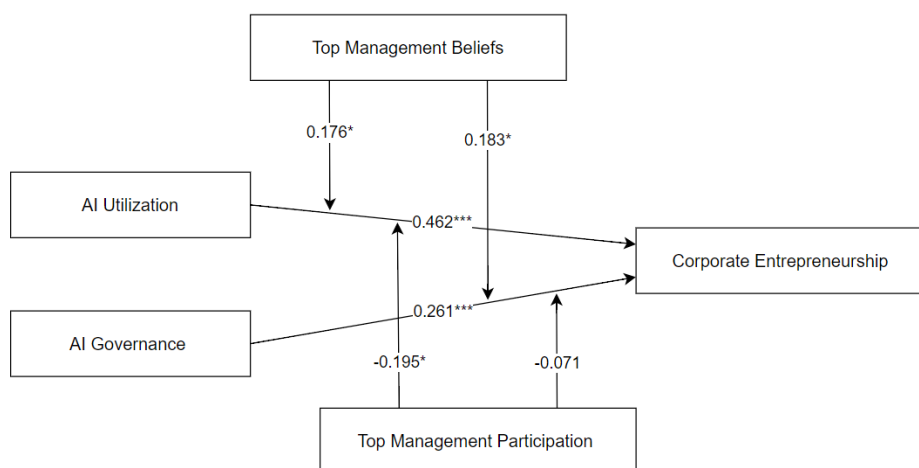
2. AIU: AI utilization; AIG: AI governance; TMB: Top management beliefs; TMP: Top management participation; CE: Corporate entrepreneurship; Gender: gender of employee; AGE: age of employee; CUL: employee literacy level; EXE: executive status; SCALE: firm scale; EAGE: firm age. MV: marker variable.

Common Method Bias

“Common method variance” refers to shared method variance associated with the measurement system of all variables in a study. Common method variance may result in artificial associations among measures because they employ a shared assessment approach rather than being related to each other based on a specific logical relationship (Podsakoff et al., 2003). The results indicate that the proportion of variance explained by a single factor is 40.109%, which is less than 50% of the total variance. Therefore, we can conclude that common method variance is not the issue (MacKenzie & Podsakoff, 2012). Due to the limitations of the single-factor method, we further employed the marker-variable technique for testing (Malhotra et al., 2006). We used the degree of preference for restaurant taste as the marker variable to assess common method bias. This variable is theoretically unrelated to at least one variable in the assessment. We adjusted the construct correlations using the lowest positive correlation between the marker variable and other variables ($r=0.017$) and computed the statistical significance of the adjusted correlations. As shown in Table 4, all significant correlations remained significant after adjustment. Therefore, we can conclude that there is no danger of common method variance.

Hypothesis Testing

We employed the analytic hierarchy process for our analysis. By systematically examining the relationships between variables, we aim to explore how AI-related factors impact the outcomes and influence of CE. The first step of the analysis typically involves controlling for variables. By including these control variables, the analysis can isolate the specific effects of AI-related factors on CE outcomes. In the subsequent steps, AI-related variables are added to the model. This allows assessing the additional variance these AI-related factors explain in predicting CE outcomes. By controlling for other relevant factors, this analysis helps attribute the observed effects explicitly to AI. Figure 2 shows the regression outcome, wherein CE is the dependent variable and TMB and TMP act as moderating variables. AI utilization and AI governance have a significant positive influence on CE. TMB plays a positive moderating role in this process, while TMP plays a negative one.



Source: This study.

Figure 2: Hypotheses testing results.

Note: * shows significance at the 0.05 level, ** shows significance at the 0.01 level, and *** shows significance at the 0.001 level.

Specifically, as shown in Table 4, the first model presents the results of a regression controlling for variables, whereas the second model includes two dimensions that measure AI. In Model 3, the moderating variable TMB and TMP is added, and Model 4 includes all variables. We examined the variance inflation factor (VIF) associated with each regression coefficient and found that the maximum VIF was 2.908, indicating that multicollinearity was not a problem.

Table 4: Results of regression analysis.

		DV = Corporate entrepreneurship			
		Model 1	Model 2	Model 3	Model 4
GEN		0.059	0.250**	0.226**	0.162*
AGE		-0.044	0.107	-0.052	0.269
CUL		-0.125	-0.048	-0.061	-0.123
EXE		0.241*	0.114	0.104	0.077
SCALE		-0.093	-0.077	-0.057	-0.065
EAGE		-0.032	-0.053	-0.070	-0.040
AIU	H1		0.632***	0.502***	0.462***
AIG	H2		0.162*	0.136+	0.261***
TMB				-0.063	-0.014

TMP			0.299**	0.296**
TMB × AIU	H3			0.176*
TMB × AIG	H4			0.183*
TMP × AIU	H5			-0.195*
TMP × AIG	H6			-0.071
F Change	1.368+	35.450***	4.922***	9.384***
R2	0.072	0.448	0.497	0.636
Adjusted R2	0.019	0.406	0.447	0.584
Changed R2	0.072	0.376	0.049	0.139

Source: This study.

Note:

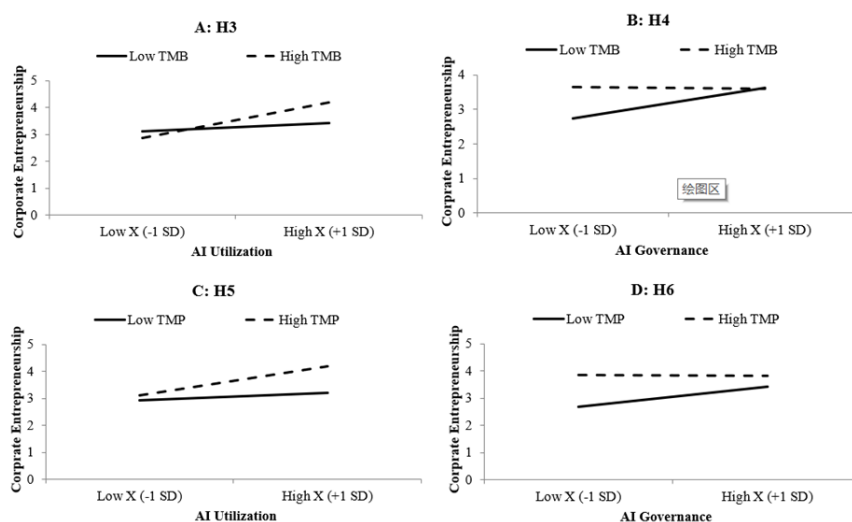
1. + shows significance at the 0.1 level, * shows significance at the 0.05 level, ** shows significance at the 0.01 level, and *** shows significance at the 0.001 level.

2. AIU: AI utilization; AIG: AI governance; TMB: Top management beliefs; TMP: Top management participation; CENTRE: Corporate entrepreneurship; Gender: gender of employee; AGE: age of employee; CUL: employee literacy level; EXE: executive status; SCALE: firm scale; EAGE: firm age.

Model 1 only contains control variables, the R-squared is 0.072, and the explanatory force is poor. Upon adding independent variables, AI utilization, and AI governance in Model 2, the R-squared value increased by 0.376. Model 3 demonstrated an increase of 0.049 in R-squared value after incorporating moderating variables, TMB and TMP. Including interaction terms in Model 4 also resulted in an increase of 0.139 in the R-squared value, thereby confirming the significance of the moderation effect. In Table 4, both Model 1 and Model 4 demonstrate that increasing AI utilization significantly positively affects CE enhancement ($\beta = 0.462$, $p < 0.001$), thereby supporting H1. AI governance also significantly promotes CE ($\beta = 0.261$, $p < 0.001$), consistent with H2.

Model 4 additionally demonstrates the moderating effects of TMB and TMP. TMB has a significantly positive moderating effect on the impact of AI utilization on CE ($\beta = 0.176$, $p < 0.05$), consistent with H3. Furthermore, TMB also positively moderates the impact of AI governance on CE ($\beta = 0.183$, $p < 0.05$), supporting H4. TMP has a negative moderating effect on both the impact of AI utilization and AI governance on CE, with TMP showing a significant moderating effect on AI utilization ($\beta = -0.195$, $p < 0.05$). However, TMP's moderating effect on AI governance is insignificant, supporting H5 and rejecting H6.

We followed the graphical procedure to analyze further the moderating effects Aiken et al. (1991)(Aiken et al. 1991 suggested. Figure 3 shows the results. According to Panel A, when TMB is high, AI utilization is positively related to CE ($\beta = 0.616$, $p < 0.001$). However, when TMB is low, the influence of AI utilization on CE is not significant ($\beta = 0.143$, $p = 0.057$). According to Panel B, AI governance has a significant positive effect on CE when TMB is low ($\beta = 0.466$, $p < 0.01$), but it has a nonsignificant effect when TMB is high ($\beta = -0.017$, $p = 0.883$). According to Panel C, AI utilization has a significant positive effect on CE when TMP is high ($\beta = 0.511$, $p < 0.001$), but it has a nonsignificant effect when TMP is low ($\beta = 0.138$, $p = 0.126$). According to Panel D, AI governance positively affects CE when TMP is low ($\beta = 0.388$, $p < 0.05$), but it has a nonsignificant effect when TMP is high ($\beta = -0.007$, $p = 0.930$).



Source: This study.

Figure 3: Plots of the Moderating Role of TMB and TMP.

DISCUSSION

Digital technologies are reshaping the form of CE. Meanwhile, strengthening and improving robust AI governance can empower firms to achieve successful business analytics solutions. Adopting an RBV perspective, this study considers AI utilization and AI governance as unique AI for firms and analyzes their impact on CE. Our research findings underscore that strengthening both AI utilization and AI governance can significantly enhance CE. Maintaining sound utilization and governance of AI can help with statistical analysis and provide decision-making information, further enhancing the firm's entrepreneurial innovation capabilities.

We also demonstrate that without sufficient commitment and involvement from top management, the potential benefits of AI may not be fully realized. Thus, we further consider the moderating effects of TMB and TMP. After the introduction of moderating variables, the effects of AI utilization and AI governance on CE remain positive and significant. Furthermore, the positive coefficients of the interaction terms between TMB and AI utilization and TMB and AI governance indicate that TMB can positively moderate the impact of AI utilization and AI governance on CE, enhancing the effect of AI on CE. However, we find that the interaction coefficients between TMP and AI utilization, as well as TMP and AI governance, are negative, and the moderating effect on AI governance is not significant. The results show that TMP weakens the promotion of CE through AI utilization and AI governance. One possible reason for this is that while TMP is considered a critical factor in driving the success of AI governance, its effectiveness may not be significant if other factors or conditions (sufficient AI expertise, technical infrastructure, or data resources) are not met.

Theoretical Implications

This study builds upon and complements previous research in two main aspects. Firstly, in line with existing literature, it confirms that AI significantly impacts promoting CE. Prior studies have already demonstrated that firms with extensive experience in utilizing AI achieve higher innovation outcomes (Rammer et al., 2022). However, this study goes beyond the broad application of AI by considering AI utilization and AI governance as distinct forms of AI. By using more AI tools and technologies, firms can identify new opportunities and create innovative solutions, enhancing business activities. Second, this study highlights the critical role of effective AI governance in fostering CE. It aligns with earlier conclusions emphasizing the importance of resource management and control for ethically harnessing AI (Winter & Davidson, 2019).

Moreover, in this study, we provide a more comprehensive explanation of how top-level management moderates the impact of AI on CE, expanding the previous literature on TMB and TMP as moderating variables. While previous literature suggests that TMT has a positive moderating effect on the impact of AI on innovation, this study presents slightly different conclusions. The findings of this study indicate that TMB serves as a positive moderating variable, aligning with previous literature. However, TMP exhibits a negative moderating effect. Specifically, a positive attitude toward digital transformation among top executives can encourage firms to invest more resources in utilizing and managing AI technology. This, in turn, can help firms acquire, control, and integrate various resources to gain a competitive advantage. Meanwhile, the negative impact of TMP shows excessive involvement may lead to poor management and use of AI.

Practical Implications

For firms, effectively using AI to enhance their innovation and entrepreneurship capabilities remains a challenge requiring ample knowledge reservoirs. The RBV theory posits that effective resource utilization is essential for a firm to succeed. Firms should actively explore and adopt various AI tools and technologies to enhance their internal innovation capabilities (Chen et al., 2021). For example, by using machine learning algorithms for data analysis and prediction, firms can identify new business opportunities and optimize workflows to improve production efficiency. Additionally, cross-departmental collaboration is crucial. Close cooperation between the IT department and business units ensures that AI technology is effectively integrated into various business processes. Simultaneously, effective AI governance in firms ensures data privacy and security while minimizing potential risks and adverse consequences. Firms need to establish transparent and responsible guidelines, such as forming an AI ethics committee that regularly reviews AI applications' compliance and social impact. These measures help protect the firm's reputation and further enhance corporate entrepreneurial development.

Furthermore, the conclusions of this study provide valuable insights for executives on how to use AI effectively. The positive moderating role of TM beliefs indicates that top managers can maintain a positive attitude toward AI technology and believe in its potential benefits. They are thus more likely to effectively implement and use AI tools and technologies to enhance entrepreneurial activities and provide significant business benefits for firms (Chalmers et al., 2021). At the same time, the negative moderating effect of TM participation suggests that simply involving top executives in AI-related activities may not be enough to ensure successful outcomes. With the continuous development and expansion of AI technology applications, executives need to obtain keen insights and adjust their strategies and decisions promptly to meet the needs of the market and customers. Moreover, top management should establish transparent and responsible corporate rules for AI governance and utilization, and ensure their implementation. Top management may approve more budget for acquiring advanced AI hardware and software, supporting employees to participate in AI-related training, or hiring experts in the AI field.

Limitations and Future Research

The limitations of this study present several compelling areas for further investigation. First, our research was conducted in China, which may limit its findings' national validity and generalizability. Given China's specific economic and institutional mechanisms, caution should be exercised when extending the current research findings to other contexts. Second, we used a questionnaire survey to collect data. Although this method is widely used, it may introduce bias. We recommend that future researchers collect data from multiple firms or obtain objective data from various sources to measure constructs and reduce errors. Third, we only collected subjective data from a single focal firm. Future research can collect data from various sources and consider using objective data to improve the robustness of hypothesis testing. Fourth, this paper only considered measuring one executive from the firm. Future studies should consider evaluating multiple executives within a firm to enhance the generalizability of the findings. Finally, since a cross-sectional design was adopted, changes in firms over different time points were not tracked. Therefore, future researchers might use longitudinal methods in their research design to observe firm changes.

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APPENDIX A: Measurement items

Variable	Item	
AI utilization (AIU)	AIU1	We use AI techniques to predict the future.
	AIU2	We develop statistical analysis using AI techniques.
	AIU3	We use AI techniques at all levels of the supply chain.
	AIU4	We use AI outcomes in a shared way to inform supply chain decision-making.
AI governance (AIG)	AIG1	We understand that AI governance may lead to the successful rollout of AI-integrated business analytics solutions.
	AIG2	We have robust AI governance in place in our firm.
	AIG3	Our firm maintains the global standard of AI governance.
Top management beliefs (TMB)	TMB1	The senior management believes that digital transformation adoption has the potential to provide significant business benefits to the firm.
	TMB2	The senior management believes that digital transformation adoption will create a significant competitive arena for firms.
Top management participation (TMP)	TMP1	The senior management actively articulates a vision for the organizational use of digital transformation.
	TMP2	The senior management actively formulates a strategy for the organizational use of digital transformation.
	TMP3	The senior management of actively establishes goals and standards to monitor the digital transformation implementation.
Corporate entrepreneurship (CE)	CE1	Our firm has spent heavily (well above your industry average) on research and development (R&D).
	CE2	Our firm has introduced a large number of new products to the market.
	CE3	Our firm has pioneered the development of breakthrough innovations in its industry.
	CE4	Our firm has entered many new industries.
	CE5	Our firm has changed its competitive approach (strategy) for each business unit.
	CE6	Our firm has reorganized operations to ensure increased coordination and communication among business units.

Source: This study.