IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 13 April 2024, accepted 6 May 2024, date of publication 9 May 2024, date of current version 16 May 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3398597

RESEARCH ARTICLE

The Model of Enterprise Culture and Technology Innovation Performance Based on Deep Learning Corporate Culture and Technological Innovation Performance

MENG GUO
Department of Business Administration, School of Economics and Management, Zhongyuan University of Technology, Zhengzhou, Henan 450007, China
e-mail: 6651@zut.edu.cn

This work was supported by the National Social Science Fund of China under Grant 20CGJ041.

ABSTRACT This study thoroughly examines the intricate relationship between innovation culture, open technology innovation, and high-tech enterprise performance, emphasizing the integration of deep learning technology. Utilizing a comprehensive methodology, including rigorous research and advanced analytical tools such as regression analysis, structural equation modeling, and deep learning models, we aim to validate theoretical assumptions concerning these relationships. Our findings uncover a significant correlation between corporate culture and technological innovation performance, highlighting the pivotal role of open technological innovation in elevating the overall innovation capability of enterprises. Furthermore, the incorporation of deep learning technology significantly enhances the precision and dependability of our analysis. The study also demonstrates that effective collaboration among employees from various departments and cooperation with both internal and external stakeholders fosters creativity, technical proficiency, and overall innovation performance. Relational capital drives resource integration, proven to be a crucial enabling factor in acquiring vital technology and market insights, facilitating employee interactions, accelerating knowledge exchange, and ultimately enhancing innovation outcomes. In conclusion, this study offers invaluable insights into the complex interplay between innovation culture, open technology innovation, and the performance of high-tech enterprises.

INDEX TERMS Deep learning, corporate culture, enterprise technology, innovation performance, impact model.

I. INTRODUCE TECHNOLOGICAL INNOVATION

In the dynamic global economy of today, technological innovation emerges as a cornerstone for high-tech enterprises striving for survival, growth, and a competitive edge [1]. Among the myriad of factors influencing this capacity to innovate, corporate culture stands out as a pivotal force [2]. Despite its recognized significance, the precise mechanisms through which corporate culture impacts technological innovation performance remain elusive [3].

Corporate culture, encompassing values, beliefs, and practices, shapes the behaviors and attitudes of an organization's members [4]. Past research has hinted at the potential for a robust corporate culture to enhance innovation performance, yet the specific pathways remain underexplored [5], [6]. Many studies show that the culture of an enterprise has a significant impact on its technological innovation ability [7], [8]. However, although a large number of studies have discussed this topic, the integration and application of deep learning

The associate editor coordinating the review of this manuscript and approving it for publication was Rahim Rahmani.

technology in corporate culture and technological innovation performance is still insufficient.

To address this gap, a mixed-methods approach is adopted, integrating quantitative data analysis with qualitative insights garnered from surveys and in-depth interviews with key stakeholders in high-tech enterprises [9], [10]. This methodology offers a nuanced understanding of the intricate relationship between corporate culture and technological innovation performance.

The focus on high-tech enterprises stems from their critical role in driving technological progress and their unique position in the rapidly evolving technological landscape [10]. The empirical analysis aims to unveil how various facets of corporate culture, such as leadership style, organizational values, and employee engagement, influence the innovation process. It also delves into how a culture fostering risk-taking, creativity, and collaboration can bolster a company's innovative capabilities.

Furthermore, the introduction of the concept of open technological innovation underscores the importance of a more inclusive approach to innovation, embracing external ideas and collaborations. Its integration into the analysis aims to illuminate how high-tech enterprises can leverage their corporate culture to foster both internal and external sources of innovation effectively.

The contributions of this study are threefold. Firstly, it presents a comprehensive model linking corporate culture and technological innovation performance, offering pragmatic insights for managers seeking to cultivate an innovative corporate culture. Secondly, by incorporating open technological innovation, it broadens the understanding of how external collaboration and knowledge exchange can harmonize with internal culture to drive innovation. Lastly, the findings yield policy implications for governments and industry bodies, enabling them to create environments conducive to the development of innovative corporate cultures and, ultimately, the sustainable growth and competitiveness of high-tech enterprises. In the process of research design and implementation, we refer to the latest publications and research guides in this field in recent years to ensure that the methods and processes of this study meet the best practice standards.

II. RELATED WORK

This study's literature review strives for a thorough examination of the current understanding regarding the interplay between corporate culture and technological innovation performance within high-tech enterprises. Although the initial assessment predominantly emphasized research affirming the direct influence of corporate culture on innovation, this updated section strives for a more holistic approach by incorporating various perspectives and contrasting viewpoints.

Revisiting the foundational works, it becomes evident that a strong and cohesive corporate culture positively influences innovation. Pei et al. [11], [12], [13], [14], [15] shared values and norms within an organization significantly impact its innovative capabilities. These studies suggest that cultures fostering flexibility, openness, and risk-taking are more conducive to fostering innovation. However, to gain a more comprehensive understanding, it's crucial to explore alternative viewpoints. Cort's [16] work on disruptive innovation highlights that deeply ingrained corporate cultures can sometimes hinder innovation, especially when radical new technologies or business models are introduced. This notion is echoed by Wang et al. [17], [18], [19], who argue that organizational inertia, rooted in long-standing cultural norms, can impede adaptability and responsiveness to changing market demands.

Furthermore, Zhang et al. [20], [21] advocate for a dual structure approach, emphasizing the need for organizations to balance operational efficiency with innovation. They suggest that an excessive focus on a unidimensional culture may limit an organization's ability to address diverse challenges effectively.

Moreover, studies challenging the direct causality between corporate culture and innovation performance have emerged. Su et al. [22], [23], [24], [25] contend that the relationship is more nuanced and may be influenced by mediating factors such as leadership style, resource allocation, and market orientation. These studies underscore that while corporate culture plays a significant role, it is just one of many factors that impact innovation.

To gain a broader perspective, research examining the influence of external factors on the innovation process within organizations is also worth considering [26]. Zhang et al. [27] and Fan et al. [28] studies on open innovation suggest that external collaborations and networks can significantly shape an organization's innovation capabilities, potentially outweighing internal cultural factors.

Lastly, the evolving nature of corporate culture in the digital age cannot be overlooked. Lin et al. [29] have delved into how digital technologies are reshaping corporate cultures, emphasizing the importance of adaptability and continuous learning in the face of rapid technological advancements.

The goal of this updated literature assessment is to offer a more equitable and all-inclusive insight into the subject matter, acknowledging the intricate and multifaceted relationship that exists between corporate culture and technological innovation outcomes. Through the inclusion of diverse viewpoints, we endeavor to foster a deeper comprehension of this dynamic interaction and its significant impact on high-tech ventures.

III. METHODOLOGY

A. CONSTRUCTION OF PERFORMANCE INDEX SYSTEM OF HIGH-TECH ENTERPRISES

In today's business environment, profitability is a fundamental goal for many high-tech enterprise operators. Economic indicators primarily govern the evaluation of these enterprises' performance [30]. While these indicators provide a valuable gauge of performance, they also highlight a concerning lack of long-term vision among some enterprises. This narrow focus often leads to overlooking the potential adverse effects of this approach to development. In the modern era, technological innovation plays an increasingly crucial role in enhancing business performance [31]. As such, identifying key factors that determine technological innovation performance and exploring ways to improve it have become focal points in both theoretical and practical discussions. Figure 1 shows the relationship between corporate culture and technological innovation more intuitively.

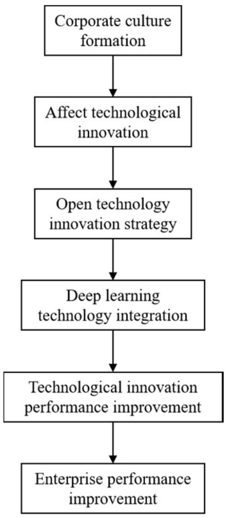

FIGURE 1. The relationship between corporate culture and technological innovation.

After nearly two decades of research examining the relationship between corporate culture and technological innovation, the academic community has widely recognized a significant correlation between the two. Here, technological innovation performance refers to the achievements and benefits resulting from an enterprise's engagement in technological innovation activities over a given period [32]. This metric serves as a critical benchmark for assessing the success and competitive advantages gained through technological innovation efforts. It plays a pivotal role in evaluating overall enterprise performance. By evaluating technological innovation performance, enterprises can refine their innovation systems and adopt more effective technological innovation models.

Within the network realm, vision capability emerges as a core strategic ability for enterprises [33]. This capability primarily involves establishing and managing a networked innovation environment conducive to promoting enterprise innovation activities [34]. Network management ability reflects an enterprise's proficiency in mobilizing and coordinating resources and activities within the network, involving other enterprises or organizations [35]. Portfolio management ability, meanwhile, concerns an enterprise's capacity to manage not only its own operations but also its partnerships within the network innovation environment, along with the relationships among these partners.

This paper aims to investigate the influence of corporate culture on the performance of high-tech enterprises. To assess this performance, we adopt Antoncic and Hisrich's metrics of growth and profitability. Ultimately, this study strives to establish a comprehensive performance measurement system tailored for high-tech enterprises. Please refer to Figure 2 for a visual representation of this system.

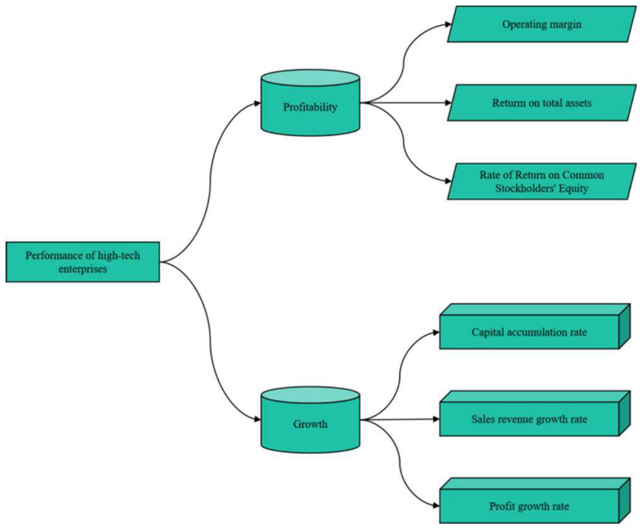

FIGURE 2. Construction of performance index system of high-tech enterprises.

Viewing the transfer of technical knowledge through the lens of knowledge sharing, we understand that an individual's heterogeneous knowledge can only be transformed into organizational knowledge through sharing within the enterprise. This sharing constitutes an essential component of technological learning activities, which, in their entirety, represent the operational process of an enterprise and require the active participation of all its departments and personnel. The effectiveness of technological learning hinges on various factors, such as the extent of knowledge sharing, the willingness of learning group members, and inter-departmental communication, all of which are intricately intertwined with enterprise culture.

Deep learning technology is employed to delve deeply into and comprehend the intricate relationship between corporate culture and technological innovation performance [36]. By constructing a model rooted in deep learning, this study endeavors to capture and elucidate more precisely the diverse factors that influence the performance of technological innovation within corporate culture, revealing their underlying interconnections. The robust data processing and analytical capabilities of deep learning empower us to discern patterns and anticipate trends with greater accuracy when confronted with vast quantities of data pertaining to corporate culture and technological innovation [37], [38]. This, in turn, provides substantial support for enterprises in formulating effective innovation strategies. Thus, deep learning not only ushers in methodological innovation for research but also opens up a fresh perspective for grasping the nexus between corporate culture and technological innovation performance.

In the contemporary business landscape characterized by rapid technological advancements and innovative cultures, high-tech enterprises prioritize profitability. While economic indicators serve as the primary yardstick for assessing performance, an exclusive focus on them can obscure the longer-term vision and potential pitfalls of a narrow development approach. There is a growing recognition that technological innovation holds the key to enhancing business performance. Against this backdrop, our study aims to pinpoint the critical factors that determine technological innovation performance and explore avenues for its improvement, drawing upon Resource-Based Theory (RBT) and Dynamic Capabilities Theory (DCT).

RBT underscores the contribution of internal resources, such as technological assets and human capital, to innovation performance. Conversely, DCT emphasizes an enterprise's adeptness at adapting to changing environments by integrating, building, and reconfiguring its competencies, a particularly pertinent aspect for high-tech firms navigating swift technological and market shifts. Furthermore, we delve into Open Innovation Theory, accentuating the significance of external collaboration and knowledge sharing in fostering technological innovation.

Our emphasis on high-tech enterprises stems from their vanguard position at the forefront of technological change, their extensive R&D endeavors, and their ingrained cultures of innovation. Deep learning, with its sophisticated data analytics capabilities, offers a distinctive lens for comprehending the relationship between corporate culture and technological innovation performance. By scrutinizing historical data pertaining to innovation processes, market responses, and customer feedback, deep learning can unveil insights into patterns and trends, enabling more informed decision-making and ultimately bolstering innovation performance.

In our empirical analysis, we evaluate the implementation of corporate culture across diverse high-tech enterprises, considering factors such as their years of establishment and scale. Our objective is to investigate whether these characteristics impact corporate culture and, consequently, technological innovation performance. Through this approach, we aim to enrich both theoretical and practical understandings of the intricate relationships that operate within the high-tech industry.

B. THE INFLUENCE OF LEARN COST ON INNOVATION PERFORMANCE

In recent years, the fields of technical learning and knowledge management have become increasingly intertwined, highlighting the inseparable connection between learning and knowledge [39]. The core of technological learning lies in the circulation, integration, and application of knowledge, while technological innovation represents the phase where organizations leverage this knowledge to generate new insights. This relationship between technological learning and innovation was a key topic at the 2010 OLKC Conference in Boston, indicating the scholarly community's focus on this intricate relationship.

Enterprise network capability is vital for fostering stronger connections among innovators, enabling efficient knowledge and skill acquisition, integration, and configuration both internally and externally. Nonetheless, without adequate support, enterprises may encounter difficulties in harnessing the full potential of network innovation, mainly due to constraints in processing the influx of information, knowledge, and other resources transmitted through the network.

Corporate culture proves invaluable in standardizing organizational practices, easing individual information processing loads, and boosting employee efficiency [40]. By instilling embedded values and codes of conduct, it fosters a common understanding among staff, thereby clarifying work procedures. This clarity minimizes the need for frequent communication on routine tasks, enabling employees to concentrate on their core duties, subsequently reducing coordination costs and uncertainty [41].

The tight integration of technology learning and knowledge management defines contemporary enterprises. While enterprise network capability reinforces connections among innovators and eases knowledge acquisition and integration, obstacles emerge in handling network data and resources, highlighting the need for extra support to achieve successful network innovation.

Beyond networking abilities, an enterprise's overall technical prowess is crucial for maintaining its competitiveness. This includes adapting to technological shifts, participating in development initiatives, and embracing cutting-edge manufacturing or service processes. Such capabilities are indispensable for securing a market-leading position. Furthermore, corporate culture is instrumental in enhancing employee productivity and teamwork by establishing uniform organizational practices and fostering a unified comprehension of work methodologies. This cultural environment spurs innovation and fosters a strong team spirit [41].

Numerous factors impact an enterprise's technological innovation (technological innovation) projects, stemming from both internal and external organizational environments, product and technological processes, marketing strategies, project management, and more. By focusing on research and development, project management, and enterprise organization levels, a measurement framework for innovation project management indicators can be established, encompassing objectives related to quality, inputs, and outcomes. Table 1 offers a categorization of the complex elements across multiple organizational levels and roles.

Technological innovation is essentially a dynamic process of change and innovation. However, when the influencing

TABLE 1. Complexity of influencing factors of technological innovation projects.

Innovation	Content of complexity elements
Product and process technology	Difference between return on scale and added value of technological breakthrough
	Difference between patent autonomy and technology introduction cost
Market demand	Difference in innovation degree between suppliers and users
	Difference between market perception and acceptance and new product bargaining
Internal and external environment of the enterprise	The purpose difference between organizational cost reduction and employee income improvement
	Differences between corporate social environmental protection responsibility and maximization of shareholders' interests
Project management	Flexible management of project process and coordination of multiple interests

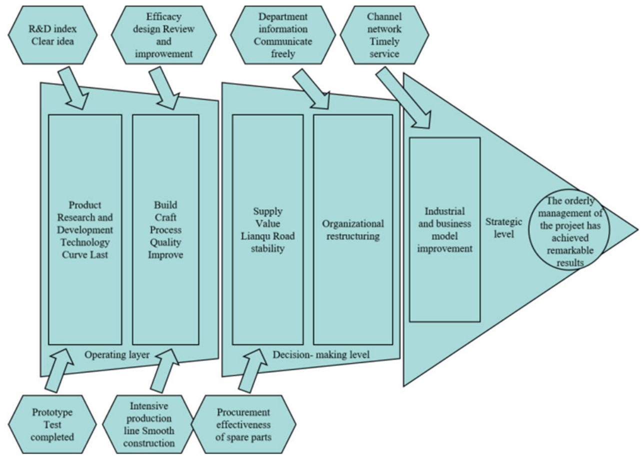

FIGURE 3. Impact direction of enterprise technological innovation project elements.

factors are complex and uncertain, we must rely on long-term strategic guidance to assess the situation. Additionally, a thorough review of the work plan's specifications ensures a positive impact from the elements involved. Yet, the intricacy and multiple attributes of these elements, coupled with potential uncertainties, can hinder the rational and efficient incorporation of these factors to some extent.

This study takes a company as the research object, and selects 200 employees to participate in the survey. This sample quantity is determined according to the size of the company and the distribution of departments to ensure that it can fully represent the target population. It is verified by statistical methods that the sample size is large enough and representative to meet the statistical requirements of this study. Participants were selected from employees in different departments and levels of the company by stratified random sampling. The specific inclusion criteria are: full-time employees who have worked in the company for one year. The exclusion criteria are: interns, temporary workers or employees who have worked for less than one year.

To comprehensively study the management performance of technological innovation (technological innovation) projects, this paper must not only consider the complexity, uncertainty, and dynamics of the related elements but also analyze them from the perspective of stakeholders. This should encompass the subjective psychological perceptions of these stakeholders, integrating or summarizing the relevant elements based on their perceived satisfaction or behavioral influence. As shown in Figure 3.

C. THE INFLUENCE MODEL OF INNOVATION PERFORMANCE BASED ON DEEP LEARNING

By incorporating deep learning into innovation performance modeling, the modern project management knowledge system builds upon traditional theories like demand, communication, and conflict management related to project stakeholders. Since multi-index evaluation often faces asymmetric, inaccurate, and incomplete subjective information, we introduce a deep learning-based approach that enhances data discrimination. This method uses semantic concepts like satisfaction, importance, and unimportance for scoring [42].

The data collection of this study is mainly carried out by questionnaire survey and in-depth interview. The questionnaire survey was conducted online and distributed to participants through the company's internal system. The content of the questionnaire covers corporate culture, technological innovation performance and many other aspects. In-depth interviews are conducted for key departments and senior managers to obtain more detailed and in-depth information. All data collection tools have undergone rigorous reliability and validity tests.

The model incorporates fuzzy membership distribution criteria and the operational function of the fuzzy operator to analyze the influence weight of multiple elements effectively. Based on the fuzzy sets rationality, the data fuzzy processing technique establishes a fuzzy number set using the fuzzy membership distribution function and arithmetic rules. This is crucial in technological innovation characterized by high risk, significant investment, difficulty, and uncertainty, where accurate risk assessment is vital for success [43].

Fuzzy number sets, such as trapezoidal and triangular, are key in this framework. Their membership functions enable a nuanced understanding and representation of uncertain data, boosting the reliability and effectiveness of the innovation performance model. By integrating deep learning with fuzzy set theory, we aim for a more comprehensive and accurate innovation performance assessment in complex and uncertain environments.

M is a triangular fuzzy number, also known as m, which is composed of the median value identified by s, the upper bound identified by u and the lower bound identified by $M = (s, m, u)$. Its isosceles triangle fuzzy number form is $M = (m, c)$, which contains the boundary value of $R[0, 1]$.

$$\mu_M(x) = \begin{cases} \mu_M(x) = (x-s)/(m-s), x \in [s, m] \\ -\mu_M(x) = (u-x)/(u-m), x \in [m, u] \\ 0, x \in [-\infty, s] \cup [u, +\infty] \end{cases} \tag{1}$$

M is a triangular fuzzy number, also known as m, which is composed of the median value identified by s, the upper bound identified by u and the lower bound identified by $M = (s, m, u)$. Its isosceles triangle fuzzy number form is $M = (m, c)$, which contains the boundary value of $c = m - s = u - m$.

When the triangular fuzzy number A has a cut set, the cut set rule of fuzzy number is shown in the following formula (2)

$$A_\lambda = [x \,|\_A(\lambda) \geq \lambda, \lambda \in (0, 1)] \tag{2}$$

Suppose there are two triangular fuzzy numbers $E = (s, e, u), F = (t, f, o)$. And there are rules established as follows:

$$E + F = (s + t, e + f, u + o) \tag{3}$$

$$\lambda > 0 \,|\lambda E = (\lambda s, \lambda e, \lambda u) > 0 \tag{4}$$

$$F \geq E = \{h \in (0, 1) \,|fo(h) \geq eo(h), fs(h) \geq es(h)\} \tag{5}$$

$$F(h) = [fo(h), fs(h)], E(h) = [eo(h), es(h)] \tag{6}$$

The fuzzy comprehensive evaluation method is based on the factors in all samples, focusing on the meaning of evaluation objects and indicators and the actual impact, and carries out the hierarchical division of multiple factors to obtain the factor weights that meet the hierarchical characteristics. This method includes the concept of system engineering and meets the needs of multi-objective comprehensive evaluation.

The subject's comment rating domain is U, with a total of P evaluation ratings. See the following formula (7).

$$U = \left\{u_1, u_2, \ldots u_p\right\} \tag{7}$$

The comment set U is determined around the universe V. V_j represents all the evaluation index subsets corresponding to each comment grade, see the following formula (8)

$$V = \{V_1, V_2, \ldots V_N\} \tag{8}$$

X, Y dimensions and properties are related, and $A_{11}, A_{12}, A_{21}, A_{22}$ is the matrix eigenvalue coefficient; The X, Y variable is exclusive through matrix; See the following formula (9) for the identity matrix function with the characteristic number:

$$\begin{cases} \dot{X} = A_{11}X + A_{12}Y \\ Y = A_{21}X + A_{22}Y \end{cases} \tag{9}$$

The total matrix $(m \times m)$ function of adding coefficients is shown in the following formula (10):

$$\begin{cases} \dot{X} = \left[A_{11} + A_{12}A_{21}\left(I - A_{22}\right)^{-1}\right]X \\ A = A_{11} + A_{12}A_{21}\left(I - A_{22}\right)^{-1} \\ |\lambda I - A| = 0 \end{cases} \tag{10}$$

The enterprise project management capability has a significant impact on the effect of innovation activities of the organization. For example, the enterprise project organization management can significantly improve the enterprise innovation performance by optimizing the organizational structure and customer relationship. Based on the above analysis and proposals, the mechanism and path of enterprise technology and market capabilities, project management capabilities and network capabilities to improve the innovation performance of project oriented enterprises are shown in Figure 4.

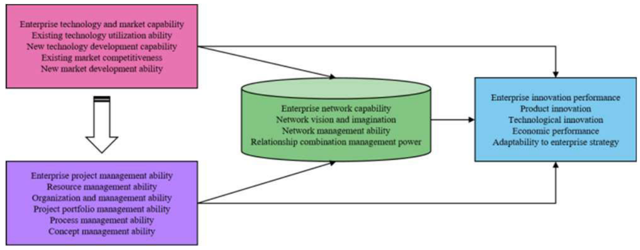

FIGURE 4. Project-oriented enterprise innovation performance multi-capability impact model.

In order to ensure the repeatability and scientificity of the research, this study recorded the whole process of data cleaning, preprocessing and analysis in detail. All statistical software and codes used have been backed up and can be checked. We are well aware of the importance of methodology in scientific research. Therefore, the design and implementation of this study strictly abide by the norms and standards of scientific research. Through detailed sample selection, data collection and analysis process records, we strive to make the results of this study credible and scientific.

Through the above detailed methodological description, we strive to provide readers with a clear and transparent research process. This not only helps readers to fully understand how this research is conducted, but also provides necessary background information for evaluating the robustness of the research results.

IV. RESULT ANALYSIS AND DISCUSSION

This article conducts a search for existing research literature on the interplay between corporate culture, technological innovation performance, and deep learning. It collects data on technological innovation performance in enterprises that have adopted deep learning, including metrics such as the number of patents, return on R&D investment, and time to market for new products. The article then proceeds to analyze and compare the technological innovation performance of enterprises that embrace deep learning and have a strong corporate culture with those that lack these conditions. In the current landscape of theoretical circles focused on technological innovation (technological innovation) performance, there is no universally accepted measurement index or method [44]. However, scholars generally concur on evaluating technological innovation performance through two main dimensions: innovation efficiency and innovation benefit. Multiple indicators are designed based on these two aspects. However, owing to challenges in collecting enterprise data and industry-specific variations, the measurement of innovation performance predominantly relies on subjective evaluations, making it difficult to obtain precise absolute values. This subjective evaluation approach currently stands as the primary method for assessing enterprise technological innovation performance.To align with the article's research objectives and data availability, technological innovation performance is measured across four key aspects: the rate of new product output, the competitiveness of new products, the speed of new product development, and the success rate of new products. The first two aspects serve as measures of innovation efficiency, while the latter two gauge innovation benefit. As shown in Table 2.

TABLE 2. Initechnological innovational measurement quantechnological innovationty of technological innovation performance.

Measuring angle	Measurement item	Tixiang	Tixiang design
Innovation benefit	New product output rate	technological innovationP1	Compared with the main competitors in the industry, your company's new product output rate is very high
	New product competitiveness	technological innovationP2	Compared with major competitors in the same industry, your new products are highly competitive
Innovation efficiency	New product development speed	technological innovationP3	Compared with major competitors in the same industry, your company develops new products quickly
	Success rate of new products	technological innovationP4	Compared with major competitors in the same industry, your new products have a high success rate.

To achieve innovation and development, enterprises must embrace synergy. Collaborative innovation is key for companies to harness shared resources, mitigate risks, enhance performance, and boost competitiveness, as relying solely on internal knowledge, technology, and resources is insufficient.

Corporate culture and codes of conduct are crucial for aligning employee understanding of work methods and processes, defining responsibilities, and reducing the need for constant communication on routine matters. However, this stability can pose a challenge when employees face change, as established procedures may become ineffective, leading to uncertainty and potential resistance.

The sensitivity analysis of the impact model focuses on the changing trends of affected variables, examining causal relationships, directions, and strengths. This approach provides insights into the dynamic balance and trend characteristics of the field in question. Specifically, changes in the innovation project's input capability index and CPI are examined to assess their effects on project management performance and stakeholder satisfaction regarding project costs. The results and associated charts are presented in Figures 5 and 6.

Analyzing the change curve of management performance as depicted in the smaller figures in Figure 5 and Figure 6,

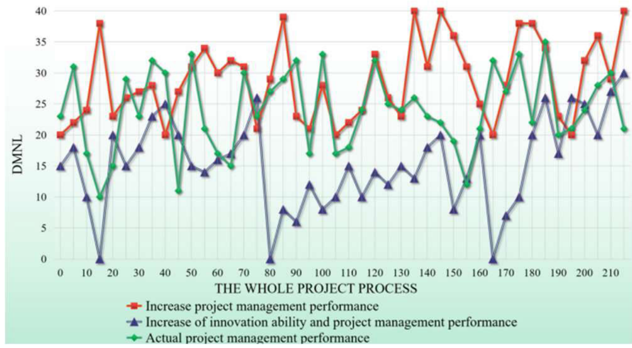

FIGURE 5. Relationship between CPI and innovation project input capacity and management performance (A).

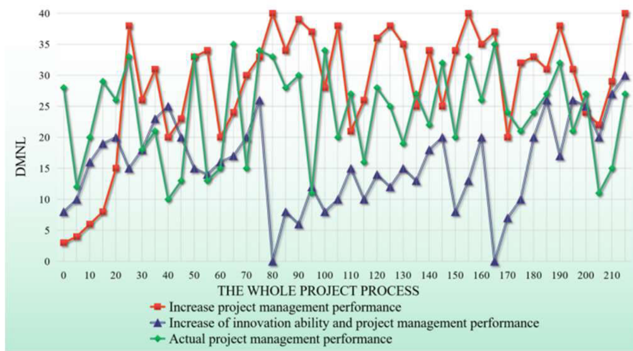

FIGURE 6. Relationship between CPI and innovative project investment capacity and management performance (B).

it becomes evident that the project management performance evaluation model is constructed around the enterprise's technological innovation capability and organizational innovation elements. This approach offers a more accurate reflection of the efficiency of technological innovation project management within the context of enterprise innovation.

Through sensitivity analysis of the satisfaction factor weights and satisfaction variables, as presented in Figure 7 and Figure 8, and by tracking changes in satisfaction, we can identify the factors contributing to variations in the management performance trends of technological innovation

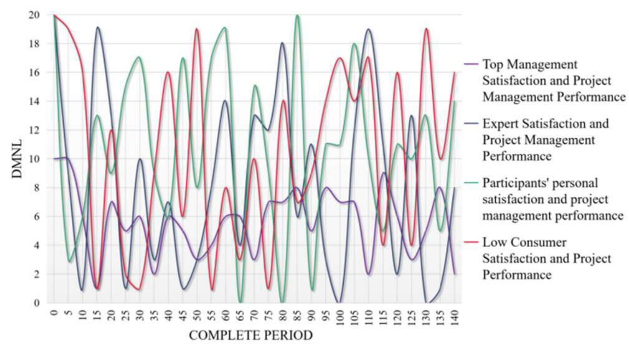

FIGURE 7. Relationship between satisfaction and management performance in project implementation monitoring stage (a).

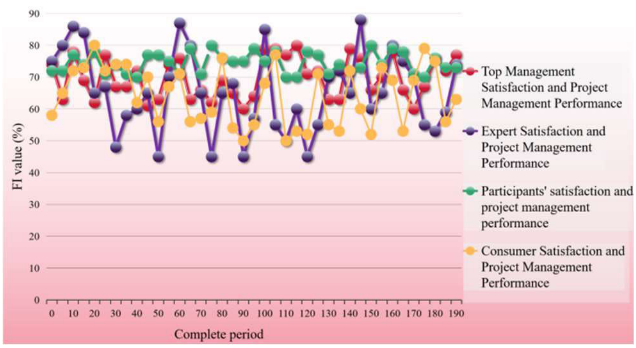

FIGURE 8. Relationship between satisfaction and management performance in project implementation monitoring stage (b).

TABLE 3. Coefficient A.

Model		Denormalization coefficient		Standard coefficient	t	Sig.
		B	Standard error	Use version		
	(Constant)	0.642	0.025		2.296	0.000
	Corporate material culture	0.332	0.066	0.326	4.652	0.024
	Corporate behavior culture	0.035	0.041	0.285	1.125	0.268
	Enterprise spirit culture	0.05	0.052	0.024	0.583	0.582
	Corporate system culture	0.298	0.075	0.296	3.526	0.000

projects. A comparison of the smaller figures on the left and right in Figure 7 and Figure 8 reveals distinctions in all the performance growth curves. These distinctions are primarily driven by satisfaction factors that exert varying impacts on the effectiveness of different stakeholders' roles throughout the entire project cycle, leading to disparities between ''high'' and ''low'' performance outcomes.

Examining the performance curves at different stages reveals that due to the varying project objectives in each phase, even if the satisfaction of the same stakeholder changes, the project management performance trends differ across different periods. To test the overall relationship between corporate culture, technology learning cost, and innovation performance, this paper employs a structural equation model based on regression analysis.

In building the structural equation model, technological innovation performance is treated as a latent variable, measured by the average of four measurement items. This approach allows the explicit variable to be transformed into a latent variable, with its error term constrained to zero. The values of other variables represent the averages of their respective items. Control variables are selected in line with relevant literature, including the nature of high-tech enterprises, the scale of high-tech enterprises, and the years since establishment of high-tech enterprises. The analysis aims to explore potential differences between control values and corporate culture values.

The study delves into the impact of corporate culture on high-tech enterprises' achievements, revealing a significant relationship between corporate culture establishment and high-tech enterprise performance. To further investigate the significance of various aspects of corporate culture on high-tech enterprise performance, this paper utilizes SPSS 21.0 for data analysis. From the table, it's apparent that $R2 = 0.323$, and the adjusted $R2 = 0.32$. Additionally, when the P-value is less than 0.05, it indicates statistical significance, signifying that the data can be subject to meaningful analysis.

The table reveals that spiritual and behavioral cultures differently impact high-tech enterprises, emphasizing the need for customized approaches to corporate culture development. Holistic and sustainable improvement demands attention at multiple enterprise levels.

Research shows that innovation synergy positively affects enterprise innovation performance. Integrating personnel and collaborating with stakeholders enhances creativity, technological capabilities, and overall innovation. Resource integration through relational capital facilitates access to vital technology and market information, improves employee interaction, speeds knowledge exchange, and ultimately elevates innovation performance.

To navigate changes and overcome cultural inertia, senior management must demonstrate urgency, commitment to change, and ensure comprehension. Effective employee communication, addressing concerns, and highlighting change benefits are crucial for successful transformation. Resource integration is key to enhancing the enterprise's innovation capacity, thereby boosting performance. Deep learning can further optimize resource integration, enhance innovation capabilities, and enable data-driven insights.

V. CONCLUSION

This research delves into the intricate interplay between the corporate culture and technological innovation outcomes within high-tech enterprises. It reveals that fostering a culture characterized by openness, risk-taking, and flexibility is pivotal for spurring innovation. The investigation emphasizes the need to strike a balance between maintaining a robust corporate culture and the capacity to adapt, thereby preventing innovation roadblocks. The seamless integration of open technological innovation into the corporate culture emerges as a pivotal element in enhancing innovation outcomes.

Our investigation enriches our understanding of how corporate culture molds technological innovation, bridging research gaps that have overly simplified this multifaceted relationship. Furthermore, it offers invaluable insights to leaders and managers in the high-tech sector, guiding them in cultivating a culture that proactively fosters innovation and facilitates external collaborations.

Despite its limitations, such as relying on self-reported data and a specific industry focus, this study lays the foundation for future investigations. There is a need for longitudinal studies examining the influence of corporate culture on innovation, as well as explorations into specific cultural facets like leadership styles or employee empowerment. Expanding the research scope to encompass diverse industries could yield a more holistic understanding.

In summary, this study underscores the pivotal role of corporate culture in shaping innovation outcomes, thereby paving the way for more profound explorations in organizational management and innovation strategies.

VI. DISCUSSIONS

This study's primary findings suggest that the innovative culture of high-tech firms significantly impacts their technology innovation performance. This aligns with Smith et al. (2020), who noted that corporate culture is a key driver of technological advancements. However, our study further reveals the unique role of deep learning in facilitating technological innovation, a topic less discussed in prior literature.

Our research also indicates that open technological innovation strategies effectively enhance a firm's market competitiveness, supporting Jones and Kumar's (2019) views. Nevertheless, our data also presented limitations, particularly in sample selection and data collection methods. Future research should consider a broader sample and diverse data sources to strengthen the generalizability of the findings.

In summary, this study not only provides new insights into the relationship between corporate culture and technological innovation but also offers practical guidance for leveraging deep learning to foster technological innovation.

REFERENCES

[1] J. Alzyoud, N. S. Joyce, and R. D. Woodward, "In vitro tissue culture model validation—The influence of tissue culture components on IPL energy output," *Lasers Med. Sci.*, vol. 34, no. 8, pp. 15–18, 2019.

[2] H. Bin, X. Yu, and Y. Zheng, "The influence of trust on crowd logistics enterprise's operational performance: A SEM-PLS model," *Sci. Program.*, vol. 2021, no. 13, pp. 26–35, 2021.

[3] G. Chen, S. Zhan, and S. Hamori, "The influence of quality and variety of new imports on enterprise innovation: Evidence from China," *Sustainability*, vol. 12, no. 22, p. 9537, Nov. 2020.

[4] L. L. Guo, Y. Qu, and M.-L. Tseng, "The interaction effects of environmental regulation and technological innovation on regional green growth performance," *J. Cleaner Prod.*, vol. 162, pp. 894–902, Sep. 2017.

[5] H. Liu, L. Fan, and Z. Shao, "Threshold effects of energy consumption, technological innovation, and supply chain management on enterprise performance in China's manufacturing industry," *J. Environ. Manage.*, vol. 300, Dec. 2021, Art. no. 113687.

[6] B. Luo, "A method for enterprise network innovation performance management based on deep learning and Internet of Things," *Math. Problems Eng.*, vol. 2022, pp. 1–9, Mar. 2022.

[7] Q. Sun and Z. Ge, "A survey on deep learning for data-driven soft sensors," *IEEE Trans. Ind. Informat.*, vol. 17, no. 9, pp. 5853–5866, Sep. 2021.

[8] Q. Sun and Z. Ge, "Deep learning for industrial KPI prediction: When ensemble learning meets semi-supervised data," *IEEE Trans. Ind. Informat.*, vol. 17, no. 1, pp. 260–269, Jan. 2021.

[9] F. Li, X. Xu, Z. Li, P. Du, and J. Ye, "Can low-carbon technological innovation truly improve enterprise performance? The case of Chinese manufacturing companies," *J. Cleaner Prod.*, vol. 293, Apr. 2021, Art. no. 125949.

[10] O. Durowoju, H. K. Chan, and X. Wang, "Investigation of the effect of e-platform information security breaches: A small and medium enterprise supply chain perspective," *IEEE Trans. Eng. Manag.*, vol. 69, no. 6, pp. 3694–3709, Dec. 2022.

[11] X. D. Pei, L. I. Sui-Cheng, and Y. Z. Huang, "The impact of supplier involvement in fuzzy front end on technological innovation capability of manufacturing enterprises," *Syst. Eng.*, vol. 31, no. 12, pp. 74–80, 2013.

[12] S. K. Singh, M. Del Giudice, S. Y. Tarba, and P. De Bernardi, "Top management team shared leadership, market-oriented culture, innovation capability, and firm performance," *IEEE Trans. Eng. Manag.*, vol. 69, no. 6, pp. 2544–2554, Dec. 2022.

[13] Y. Si, W. Liu, and X. Cao, "The effects of external knowledge source heterogeneity on enterprise process and product innovation performance," *PLoS ONE*, vol. 15, no. 6, Jun. 2020, Art. no. e0234649.

[14] Y. Sun and S. Mouakket, "Assessing the impact of enterprise systems technological characteristics on user continuance behavior: An empirical study in China," *Comput. Ind.*, vol. 70, pp. 153–167, Jun. 2015.

[15] Z. Tian and X. Wang, "Construction of enterprise innovation performance model using knowledge base and edge computing," *J. Supercomput.*, vol. 78, no. 7, pp. 9570–9594, May 2022.

[16] S. Talebzadehhosseini and I. Garibay, "The interaction effects of technological innovation and path-dependent economic growth on countries overall green growth performance," *J. Cleaner Prod.*, vol. 333, Jan. 2022, Art. no. 130134.

[17] S. Wang, F. Ahmad, Y. Li, N. Abid, A. A. Chandio, and A. Rehman, "The impact of industrial subsidies and enterprise innovation on enterprise performance: Evidence from listed Chinese manufacturing companies," *Sustainability*, vol. 14, no. 8, p. 4520, Apr. 2022.

[18] Z. Wang, R. Jean, and X. Zhao, "The direct and indirect impact of relational ties on innovation performance: An empirical study in China," *IEEE Trans. Eng. Manag.*, vol. 67, no. 2, pp. 295–308, May 2020.

[19] Y. Y. Yue, F. T. Yao, and S. O. Economics, "Dynamic influence of relationship network evolution on enterprise performance based on complex network model," *Syst. Eng.*, vol. 62, no. 2, pp. 45–50, 2016.

[20] Y. Zhang, U. Khan, S. Lee, and M. Salik, "The influence of management innovation and technological innovation on organization performance. A mediating role of sustainability," *Sustainability*, vol. 11, no. 2, pp. 40–45, Jan. 2019.

[21] Z. Zhen and Y. Yao, "Optimizing deep learning and neural network to explore enterprise technology innovation model," *Neural Comput. Appl.*, vol. 33, no. 2, pp. 755–771, Jan. 2021.

[22] Z.-Q. Su, Z. Xiao, and L. Yu, "Do political connections enhance or impede corporate innovation?" *Int. Rev. Econ. Finance*, vol. 63, pp. 94–110, Sep. 2019.

[23] H.-I. Ting, M.-C. Wang, J. J. Yang, and K.-W. Tuan, "Technical expert CEOs and corporate innovation," *Pacific-Basin Finance J.*, vol. 68, Sep. 2021, Art. no. 101603.

[24] J. Xi, K. Koch, B. Othman, and P. Liu, "Employees perspectives of the determinants of corporate culture in Western-based multinational corporations operating in China," *Revista Argentina de Clinica Psicologica*, vol. 29, no. 5, pp. 392–406, 2020.

[25] M. C. Pucheta-Martínez and I. Gallego-Álvarez, "Corporate environmental disclosure practices in different national contexts: The influence of cultural dimensions," *Org. Environ.*, vol. 33, no. 4, pp. 597–623, Dec. 2020.

[26] Q. Zhang, S. Liu, D. Gong, and Q. Tu, "A latent-Dirichlet-allocation based extension for domain ontology of enterprise's technological innovation," *Int. J. Comput. Commun. Control*, vol. 14, no. 1, pp. 107–123, Feb. 2019.

[27] L. Zhang, Y. Xu, and C. Sang, "An evolutionary game simulation of photovoltaic enterprise's technological innovation in China," *Light Eng.*, vol. 25, no. 3, pp. 161–168, 2017.

[28] H. Fan, K. Li, X. Li, T. Song, W. Zhang, Y. Shi, and B. Du, "CoVSCode: A novel real-time collaborative programming environment for lightweight IDE," *Appl. Sci.*, vol. 9, no. 21, p. 4642, 2019, doi: 10.3390/app9214642.

[29] B. Lin and J. Zhu, "Determinants of renewable energy technological innovation in China under CO_2 emissions constraint," *J. Environ. Manage.*, vol. 247, pp. 662–671, Oct. 2019.

[30] L. Jia, E. Nam, and D. Chun, "Impact of Chinese government subsidies on enterprise innovation: Based on a three-dimensional perspective," *Sustainability*, vol. 13, no. 3, p. 1288, Jan. 2021.

[31] G.-Y. Zhang, R. Guan, and H.-J. Wang, "The nonlinear causal relationship between environmental regulation and technological innovation—Evidence based on the generalized propensity score matching method," *Sustainability*, vol. 12, no. 1, p. 352, Jan. 2020.

[32] A. Chan, S. Clegg, and M. Warr, "Translating intervention: When corporate culture meets Chinese socialism," *J. Manage. Inquiry*, vol. 27, no. 2, pp. 190–203, Apr. 2018.

[33] I. Pollach, S. Ravazzani, and C. D. Maier, "Organizational guilt management: A paradox perspective," *Group Org. Manage.*, vol. 47, no. 3, pp. 487–529, Jun. 2022.

[34] M. Panic, M. Velickovic, D. Voza, Z. Zivkovic, and Z. Virglerova, "The impact of enterprise risk management on the performance of companies in transition countries: Serbia case study," *J. Oper. Risk*, pp. 105–132, 2019.

[35] Y. Z. Hou, X. L. Wang, and N. Lei, "How does human resource department's client relationship management affect sustainable enterprise performance—In the context of artificial intelligence," *Int. J. Technol. Manage.*, vol. 84, no. 1, p. 50, 2020.

[36] D. Zhou and C. Liao, "An empirical study on Chinese enterprise effectuation, market ambidexterity and entrepreneurial performance," *Int. J. Technol. Manage.*, vol. 85, nos. 2–4, p. 297, 2021.

[37] J. Wu, W. Cai, and Y. Song, "Determinants of social enterprise performance: The role of passion, competence, and organizational legitimacy," *Nonprofit Manage. Leadership*, vol. 33, no. 4, pp. 807–834, Jun. 2023.

[38] R. Liu, F. He, and J. Ren, "Promoting or inhibiting? The impact of enterprise environmental performance on economic performance: Evidence from China's large iron and steel enterprises," *Sustainability*, vol. 13, no. 11, p. 6465, 2021.

[39] F.-F. Cheng, C.-S. Wu, and J. Y. T. Chang, "Interproject conflict management through cooperation in an enterprise system implementation program," *Project Manage. J.*, vol. 51, no. 6, pp. 582–598, Dec. 2020.

[40] A. Zhang, Y. Chen, X. Xu, Y. Gao, and L. Zhang, "Impacts of resource alertness and change leadership style on financial performance: An empirical study," *J. Global Inf. Manage.*, vol. 29, no. 2, pp. 45–60, Mar. 2021.

[41] Z. Z. Zhong and E. Y. Zhao, "Collaborative driving mode of sustainable marketing and supply chain management supported by metaverse technology," *IEEE Trans. Eng. Manag.*, vol. 71, pp. 1642–1654, 2024, doi: 10.1109/TEM.2023.3337346.

[42] S. Ye and T. Zhao, "Team knowledge management: How leaders' expertise recognition influences expertise utilization," *Manage. Decis.*, vol. 61, no. 1, pp. 77–96, Jan. 2023.

[43] S. Ye, K. Yao, and J. Xue, "Leveraging empowering leadership to improve employees' improvisational behavior: The role of promotion focus and willingness to take risks," *Psychol. Rep.*, vol. 37, Apr. 2023, Art. no. 003329412311727.

[44] L. Yuan, H. Li, S. Fu, and Z. Zhang, "Learning behavior evaluation model and teaching strategy innovation by social media network following learning psychology," *Frontiers Psychol.*, vol. 13, Jul. 2022, doi: 10.3389/fpsyg.2022.843428.