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RESEARCH ARTICLE

Artificial Intelligence Capabilities and R&D Leaps: An Analysis of the Key Factors of Enterprise Innovation Transformation

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ABSTRACT

This research seeks to assess how AI capabilities and improvements in research and developmental technology impact the generation of innovative transformations in Chinese firms. This paper evaluates the impact of AI and R &D integration on innovation performance using survey data from 500 firms cutting across different industries. In the context of the research study, PLS-SEM was used to demonstrate the impact of AI talents on operation efficiency and decision-making in improving R&D outcomes, thus promoting product innovation and process improvement. Consequently, the research and development undertakings done within commercial organizations will be bound to change the approaches to innovations, with artificial intelligence needed to increase the speed at which such exercises are accomplished. The current study assists policymakers and managers in understanding how to improve innovation performance with AI and R&D.

INTRODUCTION

Advancements in artificial intelligence are another critical area that can be said to have revolutionized the business world and continue to transform how various organizations conduct their business activities, as well as the formulation and execution of their strategies. The envisioned capability of AI to cause significant transformations in organizations in terms of operational efficiency, enhanced decision-making processes and innovation in product development has positioned AI as the core element of the organizational quest for competitive advantages (Dwivedi et al., 2021; Kaplan & Haenlein, 2019). In the context of R&D, AI has been more crucial in ensuring that innovation is done within the shortest time and even developing innovations. With organizations incorporating AI automation and analytics into their operation, the dynamics between AI and R &D are essential to understanding the effect of AI on enterprise innovation evolution. Enterprise innovation transformation is a process that can be referred to as a continuous and radical transformation of processes, goods, services, and structures to sustain competition in the dynamic market environment. Research and development are the input for innovation, which provides enterprises with tools to develop new products and improve services and processes; collaboration with research institutions and other market actors improves the R&D outcome (Eurostat, 2018). AI and R&D are believed to form the primary force for organizational innovation and change, especially in industries that call for technological revolution (Chui & Malhotra, 2018).

Some researchers have noted AI's increasing role in determining enterprise innovation. It is noted that AI technologies such as machine learning, predictive analytics, and natural language processing are increasingly being applied at different stages of the innovation process, ranging from ideation to market launch (Brock & Von Wangenheim, 2019). AI helps make decisions and minimizes time-consuming, repetitive tasks, thus providing resources for more innovative research and development of both the products and the processes (Huang & Rust, 2018; Sullivan & Wamba, 2024). Furthermore, AI for decision-making improves an organization's preparedness for change by enabling market signals to be detected, customers' needs to be predicted, and resources allocated for more innovation (Zaki, 2019). Firms incorporating AI features in their R&D department commitments have witnessed increased product development productivity and improved processes (Ransbotham et al., 2018; Li et al., 2024).

Similarly, the Eurostat (2018) in Oslo Manual lays down a broad guideline for identifying, counting, and comparing innovation processes within firms; product, process, and organizational innovation are among the key focal areas. The manual further emphasizes that innovations are not limited to products but also processes and outside collaborations, which are very important in sustaining innovation performance in the long run (Eurostat, 2018). Therefore, when applied to the field of R&D, AI opportunities present enterprises with the prospects of effecting spectacular innovation strides that could give them competitive advantages in the global market.

While AI and R&D have been acknowledged to play crucial roles in promoting innovation, the current literature lacks adequate research on the interaction of AI and R&D on the innovation transformation of enterprises. Therefore, this study aims to fill this gap by examining the relationships between AI capabilities, R&D developments, and corporate innovation change within Chinese organizations. Based on data collected from 500 Chinese enterprises in several industries, this report investigates the effects of AI capabilities and R&D on organizational innovation transformation. This study aims:

1. To examine the convergent validity, discriminant validity, and reliability of the constructs, namely AI capabilities, R&D advancements, and enterprise innovation transformation of the EIT framework of enterprise innovation transformation.
2. To analyze the link between the level of AI implementation and Research and development progress that contributes to enterprises' innovation breakthrough.
3. To analyze the impact of corporate innovation change on the developments of R& D.
4. Study the dependency between AI capabilities, enterprise innovation transformation, and R&D progress.

In achieving these objectives, the research provides useful knowledge on how AI and R&D can help enhance firm creativity. Such information is useful for business managers and policymakers who must foster innovation within their organizations.

Significance of the Study

The present study contributes to the growing body of knowledge about the role of R&D and AI in driving the transformation of enterprise innovation in Chinese enterprises. This research offers much value by identifying relationships between AI enablers, research and development growth, and enterprise innovation adaptation.

- This study provides a guide to business organizations that intend to enhance innovation results by spending on AI and R&D, as it reveals that the interaction of the two results in a higher innovation performance than a single component.
- The research demonstrates the significant relationship between AI skills and R&D efforts and contributes to developing the existing theoretical frameworks.
- The study underscores the need to prioritize AI-driven R&D strategies to foster innovation in national and global markets. As governments and industries seek to develop innovation

ecosystems, the insights from this research can inform strategic decisions, particularly regarding investments in AI technologies and innovation-enabling infrastructures (Chui & Malhotra, 2018).

- The study (by providing evidence-based recommendations for enhancing innovation through AI and R&D integration) also offers implications for industries where innovation is critical to survival, such as technology, manufacturing, healthcare, and finance.

Scope of the Study

Several key dimensions may define the scope of this study:

Although the study is centered on Chinese enterprises across multiple sectors, the findings may also be relevant to other emerging economies and industries with similar technological advancements.

The research focuses on three main constructs, and each construct is measured using a set of well-validated items to capture the critical elements of AI's role in enhancing R&D and innovation processes within enterprises.

The study includes data from a diverse range of industries; this cross-industry approach enhances the generalizability of the findings, making them applicable to a wide array of enterprise settings.

Utilizing the information gathered from Chinese businesses (important decision-makers such as the findings of the study provide theoretical implications and practical significance by examining the relationships among the given constructs with the help of a statistical method known as Partial Least Squares Structural Equation Modeling (PLS-SEM), for technical specialists, R&D managers, and the senior executives.

LITERATURE REVIEW

AI and R&D to promote enterprise innovation have become two themes researched in recent years. AI technologies are developing at a very high speed, and the growing trend of their adoption in business organizations has greatly changed the innovation environment (Dwivedi et al., 2021). The current literature review will identify the roles of AI capacities, R& D undertakings, how enterprises established innovation transformation, and how prior papers and studies have been applied to establish the correlation of the factors that nurture the evolution of enterprises and enhance competitiveness.

AI Capabilities and Enterprise Innovation

AI has emerged as a revolutionary tool in today's organizations by assisting organizations in processing a large amount of data, automating processes, and enhancing decision-making. (Manyika et al., 2017). Based on definitions of AI and its application in industries, three key approaches to AI include machine learning, natural language processing, and predictive analytics, as the industries integrate the technologies to make work easier and promote innovation. For instance, the firms that apply artificial intelligence for automation are expected by Sullivan and Wamba (2024) to encounter significant improvements in productivity and process innovation. AI'sreal-time ability to analyze large amounts of data enables the organization to make the right strategic choices, shortening the innovation life cycle and creating better products (Zaki, 2019; Naz & Ahmed, 2024).

According to Kaplan and Haenlein (2019), integrating AI into product development drastically changed how a firm deals with innovation, allowing for more flexible product development processes. With the help of machine learning algorithms, organizations can permanently improve their products according to the consumers' feedback, market tendencies, and prognosis. This dynamic approach to product development reduces the time required to market the products and market relevant products and services. In the same way, the potential of AI in forecasting changes in the market and customers' behaviors contributes to organizational flexibility that helps companies be ahead of rivals through timely adaptation to emerging trends (Dwivedi et al., 2021).

However, although the advantages of AI are obvious, some research works reveal the problems of using AI in the context of enterprise innovation. For example, Ransbotham et al. (2018) observe that cultural resistance to change, the dearth of skilled human capital, and data privacy issues are challenges organizations face in AI implementation. These challenges need to be solved with specific actions, including skills investments for the workforce and effective AI governance to unlock economies of AI.

R&D Leaps and Innovation

Research and development has been understood for a long time as one of the key factors affecting enterprise innovation, as it is responsible for creating new products, improving existing processes, and creating partnerships with other organizations (Eurostat, 2018; Li & Pongtornkulpanich, 2024). The Oslo Manual also underlines the use of R&D other than technology advancement to incorporate external collaborators like universities, research institutions, and other industry players to promote innovative results. This is because collaborative R&D allows enterprises to obtain new knowledge, technological knowledge, and resources, which may result in innovation breakthroughs (Chui & Malhotra, 2018).

R&D antecedents have been widely documented in the literature, specifically the link between investments in R&D and performance in innovations. Sullivan and Wamba (2024) opine that a positive correlation exists between high investments in R&D and companies' performance in product differentiation and business process enhancements. Furthermore, R&D activities are useful for establishing long-run competitive capabilities, especially in industries emphasizing innovations. Thus, by rationalizing their expenditures on R&D, enterprises can advance and refine their products and services and adapt to the dynamic market needs (Huang & Rust, 2018).

Another trend in the literature is the application of AI to facilitate the process of R&D in the organization. As Manyika et al. (2017) stress, applying AI to R & D shortens the time for product development because developers do not spend time on the monotonous work of data analysis and simulations. Furthermore, it also plays a great role in R&D collaboration and can encourage knowledge sharing among internal and external teams and partners to improve innovation process outcomes (Kaplan & Haenlein, 2019). It is therefore expected that as artificial intelligence technologies remain a subject of development, their adoption in the R&D processes will remain a core subject of emphasis, hence promoting new forms of innovation.

AI and R&D Synergy in Driving Enterprise Innovation Transformation

Integrating AI capabilities, research, and development is increasingly important in changing enterprise innovation. When combined, AI and R&D are two significant sources of competitive advantage, significantly improving the organization's innovation performance in different aspects. AI can help streamline the R&D processes by automating data gathering, processing, and decision-making, thus freeing the R&D teams for more creative and strategic innovations (Brock & Von Wangenheim, 2019; Colvin et al., 2022). For instance, AI can help R&D teams in the following ways: determining new areas for research, estimating the success of innovations, and decreasing the time and cost involved in experimentation and trials (Chui & Malhotra, 2018).

Dwivedi et al. (2021) described, this is even more accurate when it comes to industries that have a high risk associated with the innovation processes that can be enhanced through the use of AI in R& D. In these sectors, capabilities of AI to mimic experiments, analyze big data and to develop hypothesis from unstructured data has revolutionized the way Research & Development activities are being carried out. Thus, AI reduces innovation risks and costs and helps enterprises test more and innovate faster.

However, according to the literature, there are some downsides to integrating AI and R&D, as highlighted below. Ransbotham et al. (2018) stated that while there are opportunities for AI to improve the R&D activities of an organization, such possible improvements may not be realized, especially when some organizational cultural and structural impediments to innovation are not dealt with. They create an innovative environment, set up multi-disciplinary groups, and handle ethical and governance issues with AI. However, for AI to be implemented, it is necessary to create a relationship between AI and R & D and other organizational goals and objectives to ensure that the implemented AI will greatly impact the enterprise innovation change (Zaki, 2019).

Theoretical Framework for Enterprise Innovation Transformation

The definition of innovation and the classification of innovative activities and innovative objects are presented in the Oslo Manual (Eurostat, 2018). It is concerned with product and process innovation, organizational innovation, and external partnership as part of the total change in enterprise innovation. Many papers have employed this framework to concentrate on how enterprises build innovative competence through R&D and partners. Thus, the researchers can assess the impact of AI capabilities and R&D outcomes on the range of dimensions of enterprise innovation.

In addition, Manyika et al. (2017) have introduced a conceptual model that suggests that AI is a driving force in the shifts in innovative activities across sectors. This model also suggests that AI capabilities enhance internal R&D processes while enabling the organization to respond quickly to external factors, including changes in consumers and technologies. AI integration in an organization's innovation management approach benefits those organizations in terms of efficiency in the market, flexibility and competitiveness (Kaplan & Haenlein, 2019).

The literature review section discussed above explains how AI capabilities and R&D have transformed enterprises' faces. Therefore, purchasing AI technologies that may be integrated within the R & D processes is advantageous as they accelerate innovation speeds, refine product development, and optimize the productivity of processes. However, achieving these benefits comes with organizational, cultural, and governance issues that need to be addressed, as well as integrating AI and R&D strategies with the overall business strategy. This current study extends from these ideas by investigating the moderated effect of AI capability and R&D leap on enterprise innovation transformation in Chinese enterprises. The literature review findings are highlighted in the following Table 1.

Table 1 Literature Review Matrix

Study	Year	Purpose	Methodology	Key Findings
Sullivan and Wamba (2024)	2024	To examine how AI can help firms adapt to market changes and enhance innovation	Quantitative survey and regression analysis	AI enhances firm performance and innovation by enabling adaptive responses to market changes, particularly through predictive analytics.
Dwivedi et al. (2021)	2021	To provide multidisciplinary perspectives on AI's challenges and opportunities	Quantitative, cross-sectional survey	AI offers significant opportunities for enhancing business efficiency, but challenges include ethical issues and talent shortages.

Brock and Von Wangenheim (2019)	2019	To demystify AI and its realistic applications in digital transformation	Qualitative case studies and interviews with digital transformation leaders	AI improves data collection and decision-making; realistic AI applications depend on proper integration with business strategies.
Kaplan and Haenlein (2019)	2019	To explore the implications of AI for business, focusing on voice-assisted AI (e.g., Siri)	Qualitative literature review	AI assists in product personalization and decision-making; real-world applications like Siri show how AI can transform customer interactions and business models.
Zaki (2019)	2019	To explore how digital technologies, including AI, can transform service delivery	Quantitative survey data	AI and digital transformation technologies optimize customer experiences and operational processes, leading to service innovation and improved performance.
Chui and Malhotra (2018)	2018	To explore the state of AI adoption and barriers to further integration	Quantitative and qualitative surveys and case studies	While AI adoption is advancing, barriers such as lack of skilled talent and concerns about data privacy remain significant challenges.
Eurostat (2018)	2018	To provide guidelines for measuring innovation in scientific and technological activities	Descriptive guidelines	Emphasizes the importance of measuring product and process innovation through R&D activities and external collaborations.
Huang and Rust (2018)	2018	To examine the role of AI in service industries and its impact on service innovation	Quantitative survey data	AI enhances customer service by automating processes and personalizing experiences, leading to improved service innovation.
Ransbotham et al. (2018)	2018	To explore how businesses are adopting AI to drive innovation	Quantitative survey and case studies	AI is increasingly being adopted for innovation, but organizational culture and resource limitations are significant barriers.
Manyika et al. (2017)	2017	To examine the future trends of AI, analytics, and automation	Quantitative and qualitative data analytics and case studies	AI and automation are key drivers of operational efficiency and innovation, particularly in manufacturing and service industries.

DATA

Data Collection

In the context of Chinese firms, this study investigates the relationship between R&D leaps, enterprise innovation transformation, and artificial intelligence (AI) capabilities. Technology, manufacturing, finance, and healthcare were among the areas where a sample of 500 Chinese businesses provided the data. To make sure that the responses given are the perceptions of the people directly involved in innovation processes and technology adoption, the data collection focused on the key decision makers inside these businesses, which included senior executives, R&D managers and technical managers. The data collection method used in the research was an online and paper-based survey questionnaire. The items on the questionnaire were based on the constructs obtained from two major sources (Manyika et al., 2017; Eurostat, 2018).

Constructs and Measurement

The three primary constructs and their corresponding items, as specified in the questionnaire, were:

- AI Capabilities: These are assessed by three variables (AIC1, AIC2, AIC3) that speak to the organization's effectiveness in using AI to enhance effectiveness, choice, and item improvement.
- R&D Advances: Measured by three variables, RDL1, RDL2 and RDL3, which capture the impact of R&D on product development, process improvement, and outsourcing.
- Enterprise Innovation Transformation: Evaluated by three measures (EIT1, EIT2, EIT3) focused on new product/ service development, process integration, and competitiveness.

Every statement was answered using a 5-point Likert scale ranging from 1, signifying Strongly Disagree, to 5, signifying Strongly Agree. This enables the author to make a comprehensive analysis of the contribution of AI and R&D to the aspect of innovation transformation.

The three constructs AI Capabilities (with items AIC1, AIC2, AIC3), R&D Leaps (with items RDL1, RDL2, RDL3), and Enterprise Innovation Transformation (EIT1, EIT2, EIT3) and their items, along with their explanation are provided below in Table 2.

Table 2 Main Constructs and their Items' Explanation

Construct	Item	Explanation
AI Capabilities (AIC) Items	1. AIC1: AI-Driven Operational Efficiency	It reflects the use of AI technologies to enhance operational performance and automate processes, derived from McKinsey's report's focus on automation.
	2. AIC2: AI-Enhanced Decision-Making	It relates to how AI supports strategic and operational decision-making processes, a key component of analytics and AI discussed by Manyika et al.
	3. AIC3: AI-Powered Product and Service Innovation	Refers to leveraging AI technologies to drive product and service innovation, aligning with the report's emphasis on how AI impacts innovation in products and services.
R&D Leaps (RDL) Items:	1. RDL1: R&D for New Product Development	Captures how R&D efforts contribute to developing new products, aligned with the Oslo Manual's guidelines on measuring innovation activities.
	2. RDL2: R&D for Process Improvement	Focuses on how R&D efforts lead to improvements in processes, a key area of measurement in the Oslo Manual.
	3. RDL3: R&D Collaboration with External Partners	Reflects the importance of collaborative efforts in R&D, particularly with universities, institutions, and industry partners, as

		emphasized in the Oslo Manual's discussion on partnerships and networks.
Enterprise Innovation Transformation (EIT) Items:	1. EIT1: Innovation in Product and Service Offerings	Refers to changes and improvements in products and services resulting from innovation, as highlighted in the McKinsey report and Oslo Manual.
	2. EIT2: Process Innovation and Automation	Relates to transforming enterprise processes through innovation and AI-driven automation, combining insights from McKinsey's analytics and AI focus and the Oslo Manual's process innovation measurement.
	3. EIT3: Organizational Innovation for Competitiveness	Represents innovation that transforms organizational structures or strategies to enhance competitiveness, which aligns with the Oslo Manual's broader understanding of innovation in organizational contexts.

Methodology

The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a widely used statistical method for testing complex models with latent variables. For the current study, PLS-SEM is preferred as it enables the identification of between-construct and between-item relations and the direct and indirect effects between the constructs. The assessment steps are discussed in Table 3.

Table 3 Assessment Steps

Step	Explanation
Step 1: Measurement Model Assessment	To establish the constructs' reliability and validity, the measurement model was assessedusing the following criteria: Convergent validity, discriminant validity, and internal consistency. The following criteria were used to test convergent validity: factor loadings, composite reliability, and average variance extracted; accordingly, it was determined whether the items measured the constructs of interest adequately. The discriminant validity was conducted following the Fornell and Larcker criterion. Moreover, the HTMT ratio was also calculated, and the separate nature of each construct was indicated.
Step 2: Structural Model Assessment	After validating the measurement model, the structural relationships between AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation were analyzed. In order to establish the strength of the interaction and the significance level, the path coefficients, T-statistics, and P-values were computed. This step also offered an understanding of how AI Capabilities and Enterprise Innovation Transformation support the development of R&D progress.

The survey was conducted on 800 potential respondents, and 500 filled responses were received, making the response rate equal to 62.5%. Such a response rate is deemed adequate for a PLS-SEM analysis and offers a solid basis for generalizing the population of Chinese enterprises. The analysis was done using Smart PLS 3, PLS-SEM software that enabled the evaluation of both the measurement and structural model. Based on the data analysis, this approach, backed by the methodological framework, allows us to explore the relationships between AI competencies and enterprise R&D

expenditure in China. It also means that the constructs employed in the study have been validated, and the statistical procedures used are sophisticated, thus ensuring the generalizability of the results.

RESULTS AND DISCUSSION

Table 4 Convergent Validity of AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation Constructs

Constructs	Items	Loadings	Alpha	CR	AVE
AI Capabilities	AIC1	0.874	0.823	0.894	0.738
	AIC2	0.834			
	AIC3	0.869			
Enterprise Innovation Transformation	EIT1	0.880	0.869	0.919	0.791
	EIT2	0.887			
	EIT3	0.900			
R&D Leaps	RDL1	0.894	0.840	0.904	0.758
	RDL2	0.876			
	RDL3	0.841			

Convergent validity tests shown in Table 4 indicate the extent to which each construct is related to its measures (items). This is checked through factor loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE).

All the items of the construct AI capabilities (AIC1: 0.874, AIC2: 0.834, AIC3: 0.869) have factor loadings above 0.7, indicating that each item has a good measure of the AI capabilities construct. The value of Cronbach's alpha is more than 0.7, which shows internal consistency, meaning that the items accurately measure the AI capabilities.The composite reliability (CR) value of 0.894 exceeds the threshold of 0.7, confirming the internal consistency of this construct. It is slightly more robust than the Alpha value, which aligns with composite reliability being a more comprehensive measure.An AVE value above 0.5 indicates that AI capabilities explain more than half of the variance in the indicators (items), showing strong convergent validity.

All three indicators of enterprise innovation transformation (EIT1: 0.880, EIT2: 0.887, EIT3: 0.900) are well above 0.7, implying these items are highly representative of the construct.Both values of Cronbach's alpha (0.869) and composite reliability (0.919)indicate excellent reliability. The CR value confirms the high level of internal consistency, suggesting the items work cohesively to measure innovation transformation. The AVE value (0.791)indicates that the construct captures 79.1% of the variance in its indicators, which further supports strong convergent validity.

The loadings of research and development (R&D) leaps RDL1 (0.894), RDL2 (0.876), and RDL3 (0.841) are all above 0.7, confirming that each item is a reliable representation of R&D leaps.Both Cronbach's alpha (0.840) and CR (0.904) valuesare well above the recommended thresholds of 0.7, ensuring the internal reliability of the R&D leaps construct. The AVE value (0.758) indicates that the construct explains a significant portion of the variance in the items, reinforcing its convergent validity.

In conclusion, all the constructs, i.e., AI capabilities, enterprise innovation transformation, and R&D leaps—demonstrate strong convergent validity. Their indicators are reliable, and the constructs explain a high proportion of the variance in the observed data. This suggests that the questionnaire and constructs used in the model are robust.

Table 5 Fornell Larcker Criterion for Assessing Discriminant Validity of AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation

	AIC	EIT	RDL
AIC	**0.859**		
EIT	0.394	**0.889**	
RDL	0.517	0.391	**0.871**

Table 5 assesses discriminant validity, which ensures that constructs are distinct from each other. The diagonal values represent the square root of the AVE, while the off-diagonal values are correlations between the constructs. Diagonal values for AI capabilities (0.859), enterprise innovation transformation (0.889), and R&D leaps (0.871) are higher than the off-diagonal correlations, meaning that the constructs share more variance with their indicators than with other constructs. This confirms that the constructs are distinct from one another.

Inter-construct correlations for AI capabilities and enterprise innovation transformation(0.394) have a moderate positive correlation, implying that companies with high AI capabilities will likely show some innovation transformation. A moderately strong relationship (0.517) between AI Capabilities and R&D Leaps suggests that AI plays a key role in advancing R&D efforts within enterprises. Enterprise innovation transformation and R&D leaps are moderately correlated (0.391), indicating that innovations in enterprises also contribute to significant advancements in R&D. The Fornell-Larcker criterion (Table 5) shows that each construct is unique and not overly correlated with others. The moderate correlations between AI capabilities, R&D leaps, and enterprise innovation transformation indicate that these factors are related but distinct drivers of innovation.

Table 6 Cross-loadings of AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation Items

	AIC	EIT	RDL
AIC1	**0.874**	0.348	0.498
AIC2	**0.834**	0.312	0.425
AIC3	**0.869**	0.355	0.399
EIT1	0.311	**0.880**	0.337
EIT2	0.338	**0.887**	0.300
EIT3	0.394	**0.900**	0.393
RDL1	0.423	0.353	**0.894**
RDL2	0.435	0.309	**0.876**
RDL3	0.487	0.355	**0.841**

Cross-loadings shown in Table 6 provide another way to confirm discriminant validity by showing how much each item loads onto its construct versus other constructs. For AI capabilities (AIC1, AIC2, AIC3), the loadings on the AIC construct are much higher than on EIT or RDL, confirming that these items measure AI capabilities specifically. Likewise, for enterprise innovation transformation (EIT1, EIT2, EIT3), the loadings are highest on EIT compared to AIC and RDL, confirming that the items are properly assigned. In the same way, for R&D leaps (RDL1, RDL2, RDL3), the loadings are highest on RDL, supporting that these items are valid indicators of R&D leaps. Cross-loadings confirm that each item is closely related to its construct and has a weaker relationship with other constructs, reinforcing discriminant validity.

Table 7 HeterotraitMonotraitRatio for Discriminant Validity of AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation

	AIC	EIT	RDL
AIC			
EIT	0.462		
RDL	0.613	0.450	

The HTMT ratio is another measure of discriminant validity, with values below 0.85 indicating good discriminant validity.The HTMT ratios between AI capabilities and the other constructs (EIT: 0.462, RDL: 0.613) are below 0.85.The HTMT ratio shows in Table 7 between enterprise innovation transformation and R&D leaps is also below 0.85 (0.450). In conclusion, Table 7 HTMT values confirm discriminant validity, as all the values are comfortably below the 0.85 threshold, ensuring that the constructs are distinct.

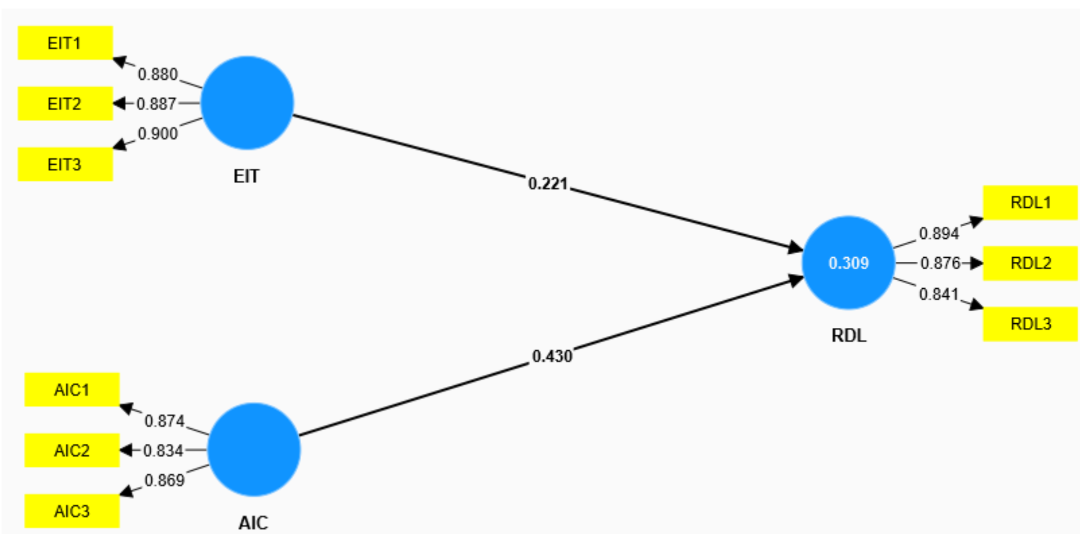

Figure 1 Measurement Model Assessment for AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation

Figure 1 likely shows the relationships between the latent variables (AI Capabilities, Enterprise Innovation Transformation, R&D Leaps) and their indicators. Given the strong factor loadings and AVE values in Table 1, the measurement model is well-fitted, showing that their indicators accurately measure the constructs.

Table 8 Path Analysis of AI Capabilities and Enterprise Innovation Transformation's Impact on R&D Leaps

Relationships	Beta	Standard deviation	T statistics	P values
AIC -> RDL	0.430	0.055	7.813	0.000
EIT -> RDL	0.221	0.050	4.467	0.000

Path analysis shown in Table 8 examines the constructs' relationships, highlighting the effects' strength, significance, and direction.The result shows a strong and significant positive relationship between AI capabilities and R&D leaps. Companies with more advanced AI capabilities are more likely to experience significant advancements in their R&D activities. The high T-statistics and low P-value indicate that this result is highly reliable. Likewise, enterprise innovation transformation has a positive and significant effect on R&D Leaps, though the impact is smaller thanthat of AI capabilities. This suggests that while innovation within enterprises contributes to R&D, the influence of AI capabilities is stronger. In conclusion, Table 8 exhibits that AI capabilities have a stronger impact on R&D leaps than enterprise innovation transformation, although both are important drivers of innovation. The statistical significance of both relationships emphasizes their critical role in fostering innovation.

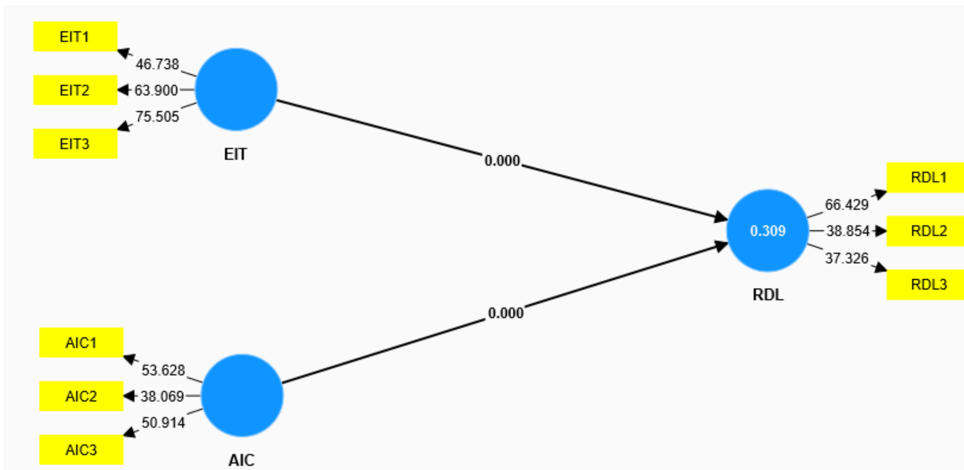

Figure 2 Structural Model Assessment of AI Capabilities, R&D Leaps, and Enterprise Innovation Transformation

Figure 2 likely visualizes the path coefficients in Table 5, demonstrating the direct effects of AI Capabilities and Enterprise Innovation Transformation on R&D Leaps. It supports the conclusion that both constructs positively impact innovation transformation.

The validity tests prove that the constructs in the model are valid and different: AI capabilities, enterprise innovation transformation, and R&D leaps. The results of the path analysis further show that AI capabilities are most influential in determining R&D leaps, and enterprise innovation transformation is also moderately influential. These results indicate that organizations that aim at increasing their innovation should invest many resources in improving their AI since it will have the most significant effect on their R&D. Also, funding for enterprise-wide innovation initiatives will also help the advancements in R & D although to a slightly lesser extent than the funding for AI capabilities. The analysis findings can be used by enterprises that want to enhance the impact of AI and R&D on innovation. From Table 9, a link between the study's objectives and the findings obtained can be ascertained.

Table 9 Objectives-to-Findings Mapping

Objective No.	**Objective**	**Achieved in**
1	Convergent Validity	Table 1
	Discriminant Validity	Table 2 and Table 4

2	AI Capabilities and R&D Leaps Relationship	Table 5 and Figure 2
3	Enterprise Innovation Transformation Impact on R&D Leaps	Table 5 and Figure 2
4	Structural Relationships	Figure 2

CONCLUSION

In order to advance the understanding of how best to initiate corporate innovation change in Chinese enterprises, this study has considered the parts that research and development (R&D) spikes and artificial intelligence (AI) skills have. AI capabilities enhance R&D outputs to higher levels because they help deliver results faster and make businesses more competitive. These capabilities are peculiar to operational effectiveness, managerial decision processes, and new product development disciplines. For this reason, R&D endeavors are essential for an organization's capability to develop new products, improve existing processes, and foster outside relationships – all of which are imperative for sustainable innovation. The findings of the path analysis show that while both constructs are important promoters of R&D success, AI capabilities have a higher direct influence on R&D Leaps than Enterprise Innovation Transformation. These findings imply that to maximize the results of innovation, businesses seeking to promote innovation should concentrate on incorporating AI technologies into their R&D plans. In summary, this study adds to the body of literature by presenting actual data on the joint effects of AI and R&D on the transformation of organizational innovation and by providing useful recommendations for company executives and decision-makers.

Policy Suggestions

Following are the policy recommendations that the study concludes:

Governments and business managers should pay more attention to the application of AI technology within the R&D departments. Policymakers also can encourage firms to adopt AI tools for partnerships, operations optimization, and new offerings.

Since businesses need a workforce that can harness AI technology to foster innovation, more funds must be provided for AI education programs in colleges and vocational schools.

To enhance the effectiveness of R&D cooperation, governments should create separate innovation centres or research and development parks where AI skills may also be promoted and transferred across industries.

To promote AI adoption, more efforts should be made to find those industries that have not adopted AI and offer relevant solutions. AI, for instance, may increase economic growth in different sectors through increasing productivity and outcomes in sectors such as health and farming.

Directions for Future Studies

1. Therefore, future research on how companies implement AI in their R&D could be done through surveys, case studies, or interviews. By so doing, a better understanding of the prospects and risks typical for many industries and businesses would be provided.
2. Recognizing the further advancement of AI in the future, future research may engage cross-sectional research to capture the dynamic process of the AI technology application and its enduring impact on corporate innovation development.

3. Although the present research is being conducted across a wide range of industries, future studies can be industry-specific, for instance, in the manufacturing or healthcare industries, to understand the impact of AI capabilities and R&D on innovation in a particular industry.

Moreover, this work could be continued to determine if there are similarities or differences in the relationships between AI, R&D, and innovation transformation under different cultural and economic backgrounds in other countries or regions.

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