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Generative artificial intelligence (GenAI) and entrepreneurial performance: implications for entrepreneurs

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Abstract

This study examines the impact of Generative Artificial Intelligence (GenAI) resources on entrepreneurial performance in China, focusing on internal integration and external collaboration mediating roles. Drawing upon Resource-Based Theory (RBT), this study proposes a theoretical model that outlines how tangible, intangible, and human resources related to GenAI affect entrepreneurial performance. GenAI internal integration and external collaboration serve as mediators. A purposive sampling technique was employed to collect data from Chinese university students who have initiated startups utilizing GenAI technologies. The Partial Least Squares Structural Equation Modeling (PLS-SEM) approach was applied to analyze data from 491 respondents. Findings reveal that GenAI's tangible, intangible, and human resources significantly foster both internal integration and external collaboration, which, in turn, positively influence entrepreneurial performance. This study contributes to the entrepreneurship and management literature by elucidating the mechanism through which GenAI resources enhance entrepreneurial outcomes, and offers practical insights for entrepreneurs on leveraging GenAI resources to bolster internal and external collaborative efforts for improved performance.

Keywords Generative artificial intelligence · Entrepreneurial performance · Resource-based theory · Internal integration · External collaboration · Chinese university student entrepreneurs

JEL classification O33 · L26 · M13 · O32 · M15

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1 Introduction

The rise of generative artificial intelligence (GenAI) technologies, represented by ChatGPT, is profoundly impacting various industries (Goel & Nelson, 2024). GenAI refers to AI systems that can generate novel content, such as text, images, audio, and video, based on learned patterns from training data (Kanbach et al., 2023; Mariani & Dwivedi, 2024). Entrepreneurs face opportunities and challenges from technological changes as a new force. GenAI provides entrepreneurs unprecedented functions and conveniences, such as collecting and analyzing a large amount of user data, optimizing internal operational processes, and improving work efficiency, making it a "super tool" for entrepreneurship (Shepherd & Majchrzak, 2022). The field of entrepreneurship, which highly relies on human creativity and subjective judgment, also confronts risks such as the rationalization of GenAI replacing human creativity and ethical challenges like algorithmic discrimination (Audretsch et al., 2023). Understanding the authentic relationship between GenAI and entrepreneurial performance, while being mindful of potential "AI washing" (Woollacott, 2024), is significant for leveraging this emerging technology to drive entrepreneurial success (Link, 2023).

Academic research on the relationship between GenAI and entrepreneurship is still in its infancy, with limited literature exploring the impact of GenAI on entrepreneurial performance, particularly identifying resources required for using GenAI (Colombelli et al., 2023; Mariani & Dwivedi, 2024). Existing studies have mainly examined the relationship between GenAI and entrepreneurship from three perspectives: conceptually, outlining the framework of "AI-enhanced entrepreneurship"; in application, discussing the specific uses of GenAI in entrepreneurship such as developing creativity, writing business plans, and conducting customer interviews; and in terms of effects, studying the impact of GenAI on entrepreneurship outcomes such as improving performance and enhancing supply chain resilience (Mikalef & Gupta, 2021; Wang & Zhang, 2024). Despite the larger resource access and innovation capabilities GenAI provides to entrepreneurs, many do not fully recognize the potential to improve entrepreneurial performance through GenAI (Tran & Murphy, 2023). The realization of GenAI's significant role in promoting business model innovation relies on the effective adoption and utilization of these technologies (Kanbach et al., 2023). While AI offers abundant opportunities, it also presents challenges, such as new entrepreneurial skills and knowledge requirements and a rethinking of entrepreneurial models and business logic (Rajaram & Tinguely, 2024).

While generative AI is still a rapidly evolving technology, there is significant value in studying its early impacts on entrepreneurship. Notably, recent studies have already begun to assess the implications of GenAI adoption on organizational performance or innovation performance, providing a foundational understanding of its current impact (Baabdullah, 2023; Singh et al., 2024; Rana et al., 2024). These studies demonstrate that meaningful insights can be gained even in the technology's nascent stages. Our research aims to capture the initial entrepreneurial responses and adaptations to generative AI, providing a baseline for future longitudinal studies as the technology matures. This study focuses on the relationship between GenAI and entrepreneurial performance, exploring how GenAI resources—including tangible, intangible, and human resources—impact entrepreneurial performance through internal integration and external collaboration. Motivated by a thorough analysis of the existing literature, which has addressed the link between AI technology and corporate performance but still lacks specific research on how GenAI acts on entrepreneurial performance, this study proposes the following research questions:

- RQ1: How do GenAI tangible resources, GenAI intangible resources, and GenAI human resources promote entrepreneurial performance?
- RQ2: Can GenAI internal integration and GenAI external collaboration enhance entrepreneurial success?

To address these questions, this research incorporates Resource-based Theory (RBT) as the theoretical framework. RBT offers a powerful perspective for understanding how enterprises can gain competitive advantage and improve performance through unique resource combinations. In the context of GenAI, RBT can help explain why and how businesses enhance their entrepreneurial performance by deploying related tangible, intangible, and human resources (Mikalef & Gupta, 2021). This study chooses the field of university student entrepreneurship as its research subject for three main reasons: the forward-looking nature of research on GenAI's influence and entrepreneurial practices among "digital natives"; the emphasis on personal agency and the role of individuals in entrepreneurship unique to student ventures; and the significance of student entrepreneurship for the healthy growth of the nation's innovation and entrepreneurship ecosystem (Wang et al., 2023).

Therefore, this study aims to construct a theoretical model of GenAI & entrepreneurial performance, exploring the relationship between GenAI resources and entrepreneurial performance and how internal integration and external collaboration mediate this relationship. Through a survey of Chinese university students who are entrepreneurs using GenAI, this study not only aims to reveal the direct impact of GenAI resources on entrepreneurial performance but also endeavors to understand how businesses can use GenAI to enhance their performance through internal integration and external collaboration. The contribution of this research lies in its extension of RBT's application in the GenAI context and its empirical guidance for entrepreneurs on using GenAI resources to foster corporate growth and enhance performance. This study enriches the theoretical research on the relationship between GenAI and entrepreneurship and offers valuable references and insights for university student entrepreneurship practice, promoting harmony and continued empowerment between humans and intelligent technology. The following sections will introduce the background, hypothesis development, research model, methodology, results, discussion, and conclusions.

2 Background

2.1 Literature review

The relationship between GenAI and entrepreneurial performance emerges as a novel subject in management and entrepreneurship research domains (Mariani & Dwivedi, 2024; Wales et al., 2023). Studies have progressively unfolded, rendering preliminary theoretical groundwork and empirical evidence for the sector's evolution. Shepherd and Majchrzak (2022) conceptualized an "AI-enhanced entrepreneurship" model that integrates GenAI with entrepreneurship, leveraging mutual advantages. Obschonka and Audretsch (2020) discuss the potential risk of GenAI rationalizing over human creativity. Vecchiarini and Somià (2023) examined GenAI's specific application in entrepreneurship education. Mikalef and Gupta (2021) investigated GenAI's influence on organizational creativity and enterprise performance. While previous studies laid the foundation for understanding the relationship between GenAI and entrepreneurship, notable gaps remain.

Earlier research scarcely inspected resource conditions requisite for GenAI utilization (Rajaram & Tinguely, 2024). Tran and Murphy (2023) highlighted that numerous entrepreneurs fail to recognize the potential to enhance performance using GenAI. Kanbach et al. (2023) posited that the efficacy of GenAI relies on its effective application and utility. Resource allocation is pivotal in achieving this goal. Current literature inadequately focuses on the mechanisms through which GenAI affects entrepreneurial performance. Shepherd and Majchrzak (2022) emphasized conceptual dimensions, while Mikalef and Gupta (2021) focused more on the effects within the entrepreneurial domain, with scant examination of the intrinsic mechanisms of such impacts. Existing studies rarely address the mediating roles of variables, which hampers a profound understanding of the relationship between GenAI and entrepreneurial performance. Chen et al. (2022) studied the impact of artificial intelligence on e-commerce enterprise performance yet did not consider GenAI's internal integration and external collaboration.

Addressing these deficiencies, this study endeavors to refine the understanding of the relationship between GenAI and entrepreneurial performance by constructing a GenAI & entrepreneurial performance theoretical model. This research, framed by Resource-Based Theory (RBT), definitively classifies GenAI resources and probes the pathways through which these resources, via internal integration and external collaboration, impact entrepreneurial performance. Empirical research on Chinese university student entrepreneurs utilizing GenAI tests the direct effects of GenAI resources on entrepreneurial performance and unveils how internal integration and external collaboration serve as mediating variables, enhancing the connection between GenAI resources and entrepreneurial performance.

Building upon and refining previous research, this study further enriches the theory and empirical investigation regarding the relationship between GenAI and entrepreneurial performance. By exploring the categorization of GenAI resources, their functional mechanisms, and the mediating roles of internal integration and external collaboration, the study addresses academia's demand for in-depth exploration in this field and provides practical guidance and recommendations for entrepreneurship practice.

2.2 Research constructs definitions

This study focuses on core constructs, including resources related to GenAI, internal integration, external collaboration, and entrepreneurial performance. These constructs are defined and applied in this study based on existing academic literature, with adjustments and expansions made following the specific context of our research.

GenAI Resources: GenAI resources are categorized into three sub-constructs: tangible resources (GenAI Tangible Resources), intangible resources (GenAI Intangible Resources), and human resources (GenAI Human Resources). Tangible resources refer to the hardware, data, and tools necessary for applying GenAI technology. Intangible resources include the culture of innovation, strategies, and recognition of the importance of GenAI. Human resources address the enterprise's understanding, planning, and implementation capabilities regarding applying GenAI (Chen et al., 2022; Mikalef & Gupta, 2021).

GenAI Internal Integration: Internal integration indicates how an enterprise utilizes GenAI to optimize decision-making, operational processes, and teamwork. It is a crucial mediator in maximizing the utility of resources (Lin, 2022; Lin & Lin, 2008; Shepherd & Majchrzak, 2022).

GenAI External Collaboration: External collaboration highlights how enterprises employ GenAI technology for knowledge exchange, resource sharing, and market development with external partners. It constitutes another vital pathway for accelerating innovation and enhancing market competitiveness (Lin, 2022; Kanbach et al., 2023).

Entrepreneurial Performance: Entrepreneurial performance is the aggregate outcome of an enterprise's use of GenAI resources and capabilities, resulting in increased market share, return on investment, revenue growth, and net profit (Yeh et al., 2021; Wang et al., 2023).

2.3 Resource-based theory

Resource-Based Theory (RBT) provides this study's theoretical underpinning and perspective. RBT posits that an enterprise's unique internal resources and capabilities are the decisive factors for sustained competitive advantage (Barney, 1991). RBT highlights that advantage originates within the enterprise, which can achieve profitability by controlling distinct resources and capabilities. RBT concentrates on how enterprises use scarce, irreplaceable, and inimitable strategic resources to forge core competencies (Peteraf, 1993).

RBT offers a valuable lens through which to comprehend how GenAI impacts entrepreneurial performance. Entrepreneurial activities carry high uncertainty, and GenAI, as an emerging technology, can mitigate this uncertainty. According to RBT, entrepreneurs can leverage GenAI resources to gain informational and innovative advantages, integrating these into organizational capabilities that enhance entrepreneurial performance (Chen et al., 2022; Mikalef & Gupta, 2021). The scarcity and inimitability of GenAI resources help entrepreneurs establish unique advantages (Kanbach et al., 2023).

From an RBT viewpoint, this study differentiates GenAI resources into three dimensions: tangible, intangible, and human resources (Barney, 1991). These resources are essential for entrepreneurs applying GenAI. GenAI tangible resources, including hardware, data, and tools, provide the technical foundation for GenAI applications (Mikalef & Gupta, 2021); GenAI intangible resources encompass an innovative culture, strategies, etc., which can accelerate GenAI applications and innovation; GenAI human resources focus on the personnel's understanding and application abilities of GenAI, crucial for transforming technology into productivity (Chen et al., 2022).

RBT suggests that enterprises must also foster adaptive organizational processes to integrate resources into capabilities output (Eisenhardt & Martin, 2000). This study posits GenAI internal integration and external collaboration as mediating variables, examining how GenAI resources affect entrepreneurial performance through these two pathways. RBT provides a theoretical foundation for understanding the relationship between GenAI resources and entrepreneurial performance and guides the construction of this study's model and hypotheses.

3 Hypothesis development and research model

3.1 GenAI tangible resources, internal integration and external collaboration

Resource-based theory (RBT) suggests enterprises can achieve above-normal profits by controlling unique resources (Peteraf, 1993). As scarce strategic assets, GenAI's tangible resources provide entrepreneurs with information and innovation advantages that enhance entrepreneurial performance (Mariani & Dwivedi, 2024). These resources, which include essential hardware, data, and software tools, create the technical foundation for the GenAI application (Mikalef & Gupta, 2021), without which widespread implementation of GenAI is challenging. Tangible resources, such as cloud computing and big data analysis hardware, provide the infrastructure for collecting, storing, and analyzing vast amounts of data (Chen et al., 2022), whereas software tools for text, image, and voice generation support the innovative application of GenAI in various domains (Shepherd & Majchrzak, 2022). Providing the necessary technical foundation and data support enables enterprises to utilize GenAI for decision-making better, optimize processes, and enhance team coordination, improving internal integration efficiency and effectiveness. Thus, we propose the following hypotheses:

H1: GenAI tangible resources positively influence GenAI internal integration.

Advanced hardware and rich data resources are prerequisites for implementing AI technologies and driving enterprise innovation. By integrating tangible resources, enterprises can enhance internal process optimization and decision support, promoting technical exchanges and resource-sharing with external partners (Barney, 1991; Eisenhardt & Martin, 2000). Substantial GenAI tangible resources provide technical support and assurance for external collaboration, enhancing market competitiveness and innovation capacity. GenAI tangible resources facilitate internal decision-making, workflow optimization, and innovative applications (Kanbach et al., 2023). Voice recognition and machine translation technologies can assist team collaboration (Vecchiarini & Somià, 2023), while automation tools and data analysis instruments increase internal efficiency (Winkler et al., 2023). Furthermore, tangible resources improve collaboration with external partners, such as knowledge sharing and resource integration (Lin & Lin, 2008). Entrepreneurs equipped with GenAI tangible resources are likelier to establish mutual trust with partners and jointly develop new opportunities. Therefore, we propose the following hypothesis:

H2: GenAI tangible resources positively influence GenAI external collaboration.

3.2 GenAI intangible resources, internal integration and external collaboration

GenAI intangible resources, as strategic assets, propel innovation related to GenAI and foster internal integration and external collaboration. Intangible resources such as a culture of innovation and strategic planning provide direction and momentum for GenAI's application and internal process optimization (Mikalef & Gupta, 2021). These resources encompass the enterprise's recognition of GenAI innovation, innovative strategies, and a supportive culture for GenAI. Such a culture can stimulate employees to explore new ways to apply GenAI, accelerating the sharing of internal knowledge and technology integration (Giuggioli & Pellegrini, 2023). Intangible resources play a pivotal role in the enterprise's acknowledgment of GenAI's value and in fostering an environment that nurtures GenAI innovation (Khalid, 2020). Enterprises with a culture and strategy of innovation in GenAI are more proactive in seizing market opportunities provided by GenAI, incorporating them into product and service innovation (Winkler et al., 2023). An innovative culture enables consensus formation on the value of GenAI and resource allocation for its learning and application, facilitating its deep integration into operations and management (Abaddi, 2023; Ge & Zhao, 2022). Innovative strategies guide enterprises in employing GenAI to improve internal decision processes and operational efficiency (Xu & Zhang, 2021). Therefore, we propose the following hypothesis:

H3: GenAI intangible resources positively influence GenAI internal integration.

Intangible resources facilitate knowledge exchange and resource sharing between the enterprise and external partners. A strong base of intangible resources helps the enterprise integrate internal resources, promoting collaboration and exchange with external partners (Mikalef & Gupta, 2021). Accumulating and applying intangible resources, especially in innovation capabilities and technical knowledge, provide a unique perspective and approach to advancing new technology development and application (Eisenhardt & Martin, 2000). Such capabilities promote the efficiency of internal integration and strengthen synergy with external partners, jointly propelling technological innovation and market expansion. The enterprise's reputation and proprietary knowledge attract potential partners, establishing and sustaining stable cooperative relationships (Lin & Lin, 2008). Deep understanding and strategic approaches to GenAI benefit the enterprise in negotiations, pushing for successful collaborative projects (Kanbach et al., 2023). An innovative culture promotes shared ideologies with partners, aiding better GenAI utilization for knowledge exchange and market development (Gupta & Yang, 2023; Upadhyay et al., 2023). Thus, we propose the following hypothesis:

H4: GenAI intangible resources positively influence GenAI external collaboration.

3.3 GenAI human resources, internal integration and external collaboration

Possessing a wealth of GenAI human resources enables entrepreneurs to better leverage these technologies for internal operations and decision-making (Rajaram & Tinguely, 2024). Employees' understanding of the application domains and methods for GenAI can guide enterprises in selecting the appropriate GenAI tools to optimize specific business processes (Abaddi, 2023). Furthermore, the ability of employees to plan for and receive training in GenAI usage is crucial for realizing GenAI internal integration (Mikalef & Gupta, 2021). When staff possess the skills to drive product and service innovation with GenAI, it becomes easier for the enterprise to consider GenAI as a strategic resource for internal innovation (Chen et al., 2022). Human resources skilled in GenAI can effectively promote knowledge sharing within the enterprise, strengthen team collaboration, and enhance the efficiency of internal integration (Lin & Lin, 2008). With adequate GenAI understanding, employees can develop practical GenAI use plans, increasing the likelihood of the enterprise optimizing its internal operations and management through GenAI (Wang et al., 2023). GenAI human resources provide a talent guarantee for the ongoing learning and application of GenAI, helping to efficiently align GenAI with internal processes and demands. The mastery of GenAI knowledge and training by the management and staff facilitates the planning and execution of GenAI projects, promoting the integration of GenAI with current business processes and systems (Xu & Zhang, 2021). Therefore, we propose the following hypothesis:

H5: GenAI human resources positively influence GenAI internal integration.

GenAI human resources also aid entrepreneurs in constructing collaborative networks with external partners. Employees' comprehension of GenAI applications eases the identification of external partners whose specialized knowledge matches the enterprise's needs. The capability of employees to plan for GenAI applications can better shape the collaboration routes with external partners (Giuggioli & Pellegrini, 2023). Insufficient GenAI knowledge and application experience may hinder effective communication and smooth cooperation with external partners (Khalid, 2020). Employees receiving relevant GenAI training will likely establish technical exchanges and experience sharing with external partners (Mikalef & Gupta, 2021). Staff with GenAI application skills are poised to actively engage external partners in market development and business model innovation (Gupta & Yang, 2023). GenAI human resources lays the foundation for implementing external collaboration, helping the enterprise expand its ecosystem and acquire more external support (Barney, 1991; Vecchiarini & Somià, 2023). A robust human resource foundation assists in building and maintaining stable cooperation relationships with external partners, promoting resource sharing and market expansion (Kanbach et al., 2023). Effective GenAI human resources ensure that GenAI is deeply integrated into the enterprise's internal processes and external networks. Hence, we propose the following hypothesis:

H6: GenAI human resources positively influence GenAI external collaboration.

3.4 GenAI internal integration, external collaboration and entrepreneurial performance

GenAI internal integration focuses on how enterprises utilize generative artificial intelligence technologies to optimize decision-making, improve workflows, and boost collaboration efficiency. Internal integration can help entrepreneurs utilize these technologies for data analysis to support decision-making (Winkler et al., 2023), streamline internal operations (Kanbach et al., 2023), enhance team collaboration (Vecchiarini & Somià, 2023), and innovate products or services (Abaddi, 2023). Such applications can improve entrepreneurs' market responsiveness and operational efficiency, enhancing entrepreneurial performance, such as growth in market share and return on investment. GenAI internal integration directly impacts entrepreneurial performance, as it determines to what extent an enterprise can utilize these emerging technologies to increase operational efficiency, reduce costs, and stimulate employee creativity (Chen et al., 2022). Artificial intelligence integration can significantly improve enterprise productivity and innovation capability (Mikalef & Gupta, 2021). Enterprises with AI capabilities are more likely to achieve superior operational performance. Applications of GenAI provide new tools for enterprises to optimize internal processes. Hence, we propose the following hypothesis:

H7: GenAI internal integration has a positive impact on entrepreneurial performance.

GenAI external collaboration emphasizes how enterprises leverage these emerging technologies for market development and resource integration with external partners. External collaboration can be a pathway for entrepreneurs to gather more resources and capabilities, further enhancing entrepreneurial performance (Barney, 1991; Peteraf, 1993). Through GenAI-driven partnerships, entrepreneurs can efficiently analyze external data, exchange knowledge, optimize resource-sharing processes, propel market development, and formulate better collaborative strategies (Gupta & Yang, 2023). These GenAI applications can help entrepreneurs expand external networks, secure more market intelligence, technical support, and other resources, establish differentiated advantages and boost entrepreneurial performance (Lin & Lin, 2008; Upadhyay et al., 2023). GenAI facilitates enterprises in analyzing vast external information and identifying high-value collaborators. Applications of AI technology aid enterprises in improving relations with customers and suppliers, expanding collaboration networks, and acquiring more external support (Lin & Lin, 2008). Enterprises with robust AI capabilities are likelier to actively share knowledge and open innovation with partners (Wamba, 2022). GenAI offers new avenues to find and evaluate partners, providing new technological means for cooperation (Kanbach et al., 2023). Therefore, we propose the following hypothesis:

H8: GenAI external collaboration has a positive impact on entrepreneurial performance.

Based on Resource-Based Theory, generative artificial intelligence, and entrepreneurial performance literature, this study proposes the GenAI & entrepreneurial performance research model (Fig. 1). To enhance the robustness of our model, we have included gender, age, major and university location as control variables (Huang et al., 2022; Upadhyay et al., 2022; Wang et al., 2023).

4 Methodology

4.1 Data collection

In our study exploring the application of GenAI in university student entrepreneurial activities and its impact on entrepreneurial performance, we utilized purposive sampling. We collaborated with entrepreneurship schools from five universities located in different regions of China: three in Eastern China (Zhejiang), one in Northern China (Beijing), and one in Western China (Sichuan). These universities were selected to provide geographic diversity and represent different levels of economic development across China. This approach aided the effective identification and invitation of participants with rich GenAI entrepreneurship experience, ensuring data representativeness and professionalism (Chen et al., 2022).

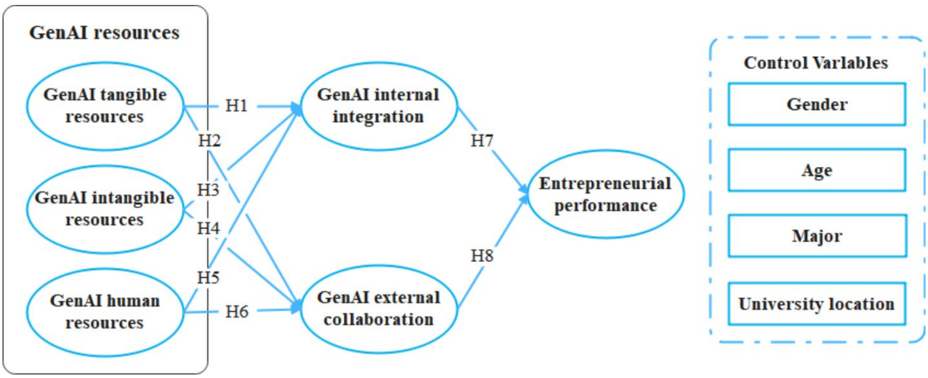

Fig. 1 GenAI & entrepreneurial performance research model

Considering the abstract nature of the variables under study, such as GenAI's tangible, intangible, and human resources, we used questionnaire surveys as the primary data collection tool. This method efficiently gathers a significant amount of subjective and perceptual data and addresses geographical limitations, enabling broader participant reach (Mikalef & Gupta, 2021). Questionnaires were distributed online via the Wenjuanxing platform and disseminated through various channels, including social media and email, to ensure wide distribution among target respondents (Ben Youssef et al., 2021).

The questionnaire was structured into two main sections: the first collected respondent demographics to assess sample characteristics; and the second centered around the six core constructs of our research model for subsequent data analysis and hypothesis testing. To ensure targeted surveying and data quality, we included a screening question on participation in GenAI entrepreneurial activities; responses of 'no' concluded the questionnaire to prevent data bias. The first question set the context for our study by asking respondents which GenAI tools their teams had used. Incentives for survey completion and data confidentiality were promised to encourage a high response rate and data integrity (Upadhyay et al., 2022).

Data collection spanned from December 2023 to February 2024, initially yielding 621 questionnaires. We acknowledge that this represents an early stage in GenAI adoption, and findings should be interpreted with this context in mind. After filtering and removing incomplete cases, we obtained 491 valid responses (Table 1), achieving a response rate of 79.07%. This sample size significantly exceeded the minimum requirement calculated via G*Power software (92 responses), providing robust data support for our research (Amani et al., 2024).

We conducted follow-up interviews with ten respondents in July 2024 to understand the concerns about their English language proficiency and internet access. Respondents confirmed that Chinese internet service providers, such as China Telecom International and China Mobile, offer services that allow entrepreneurs to apply for legitimate international internet access. Additionally, respondents highlighted the use of automatic translation tools, such as Google Translate, Microsoft Translator, Tencent Translate, Youdao Translate, Baidu Translate, and ChatGPT-4, which provide comprehensive translation services, enabling effective access and understanding of English-language content.

4.2 Measurement scales

To ensure the validity and reliability of our measurement scales, we developed and validated them systematically, informed by a broad literature review (Ben Youssef et al., 2021). We extracted key indicators that meticulously describe the core study concepts of GenAI - tangible, intangible, and human resources, internal integration, external collaboration, and entrepreneurial performance. After internal discussions, we consolidated these indicators into a draft scale, which was reviewed and refined by a cross-disciplinary panel of experts from fields including management, innovation studies, and artificial intelligence.

This panel provided feedback leading to the refinement of the measurement items, ensuring relevance and eliminating ambiguity (Wang et al., 2023). The clarity and simplicity of the scales were paramount. The finalized version of the scale (Table 2) was assured for cross-language equivalence through back-translation.

The scales employed a seven-point Likert scale (1==strongly disagree; 7==strongly agree) to capture respondents' agreement levels accurately. The foundations for these scales

Table 1 Profile and characteristics of respondents

Attributes	Characteristic	Frequency	%
Have you participated in entrepreneurial activities related to GenAI?	Yes	491	100
Gender	Male	348	70.9
	Female	143	29.1
Age	<19	86	17.5
	19–23	255	51.9
	24–28	94	19.2
	>28	56	11.4
Family background in entrepreneurship activities	Yes	216	44
	No	275	56
Major	Philosophical	0	0
	Economic	48	9.8
	Law	0	0
	Education	0	0
	Literature	29	5.9
	History	34	6.9
	Natural	35	7.1
	Engineering	118	24
	Agronomy	0	0
	Medicine	61	12.4
	Management	135	27.6
	Arts	31	6.3
Which GenAI tools has our team utilized?	Text generation tools (such as ChatGPT, Wenxin Yixian, Xunfei Xinghuo, etc.)	348	70.9
	Image generation tools (Midjourney, Stable Diffusion, etc.)	169	34.4
	Audio generation tools	136	27.7
	Data analysis and prediction tools	130	26.5
	Robotic Process Automation (RPA) tools	47	9.6
	Augmented Reality (AR) and Virtual Reality (VR) tools	63	12.8
	Other generative artificial intelligence tools	80	16.3
University location	Northern China	146	29.7
	Eastern China	244	49.7
	Western China	101	20.6

were supported by highly-cited literature, ensuring theoretical soundness and alignment with contemporary research concepts related to GenAI (Chen et al., 2022; Mikalef & Gupta, 2021). Data analysis methods, bias tests, and results will be presented in subsequent steps.

4.3 Data analysis

The Partial Least Squares Structural Equation Modeling (PLS-SEM) was utilized for data analysis to explore the relationships between GenAI resources, internal integration, external collaboration, and entrepreneurial performance. PLS-SEM was chosen due to its effective-

Table 2 Measurement scales

Questionnaire	Loadings	VIF
GenAI tangible resources (GTR) (Adapted from Chen et al., 2022; Mikalef & Gupta, 2021); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.856 CRA: 0.861 CRC:0.902 AVE: 0.698 Mean: 4.804 SD: 1.603		
GTR1: We possess the hardware equipment (such as computers) necessary to apply GenAI.	0.839	2.097
GTR2: We have access to the data required to operate GenAI.	0.832	1.956
GTR3: We own the tools (or software) to apply GenAI.	0.847	1.920
GTR4: We have allocated sufficient funding for the implementation of GenAI.	0.824	1.903
GenAI intangible resources (GIR) (Adapted from Mikalef & Gupta, 2021); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.878 CRA: 0.880 CRC:0.916 AVE: 0.732 Mean: 4.375 SD: 1.703		
GIR1: We recognize the importance of innovation in GenAI.	0.850	2.234
GIR2: We have strategies in place for GenAI's innovation.	0.865	2.274
GIR3: We introduce new GenAI to enhance our entrepreneurial performance.	0.865	2.218
GIR4: We actively implement GenAI initiatives to seize development opportunities.	0.842	2.043
GenAI human resources (GHR) (Adapted from Chen et al., 2022); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.860 CRA: 0.860 CRC:0.905 AVE: 0.704 Mean: 4.595 SD: 1.769		
GHR1: We understand the scope of applications for GenAI.	0.840	1.995
GHR2: We can devise plans for the use of GenAI.	0.846	2.020
GHR3: We can obtain training for the use of GenAI.	0.838	1.981
GHR4: We are capable of utilizing GenAI.	0.832	1.974
GenAI internal integration (GII) (Adapted from Lin, 2022; Lin & Lin, 2008); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.881 CRA: 0.883 CRC:0.9813 AVE: 0.678 Mean: 4.674 SD: 1.678		
GII1: We use GenAI for data analysis to support internal decision-making.	0.813	1.991
GII2: We use GenAI to optimize internal operational processes.	0.804	1.973
GII3: We use GenAI to enhance work efficiency.	0.842	2.214
GII4: We use GenAI to facilitate collaboration among team members.	0.831	2.138
GII5: We use GenAI for product or service innovation.	0.825	2.027
GenAI external collaboration (GEC) (Adapted from Lin, 2022); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.899 CRA: 0.901 CRC:0.925 AVE: 0.713 Mean: 4.695 SD: 1.682		
GEC1: We leverage GenAI to improve the analysis efficiency of external data.	0.834	2.259
GEC2: We leverage GenAI to facilitate knowledge exchange with external partners.	0.845	2.353
GEC3: We leverage GenAI to optimize resource-sharing processes with partners.	0.809	1.945
GEC4: We leverage GenAI to promote market development with partners.	0.851	2.415
GEC5: We leverage GenAI to optimize collaboration strategies with partners.	0.881	2.769
Entrepreneurial performance (EP) (Adapted from Yeh et al., 2021; Wang et al., 2023); (1 = strongly disagree; 7 = strongly agree)		
Alpha: 0.889 CRA: 0.889 CRC:0.918 AVE: 0.692 Mean: 4.426 SD: 1.627		
EP1: Following the use of GenAI, our market share has continuously grown.	0.826	2.109
EP2: Following the use of GenAI, our investment returns have continuously grown.	0.847	2.305
EP3: Following the use of GenAI, our entrepreneurial revenue has continuously grown.	0.832	2.116

Table 2 (continued)

Questionnaire	Loadings	VIF
EP4: Following the use of GenAI, our net profit has continuously grown.	0.826	2.112
EP5: Following the use of GenAI, our market competitiveness has significantly enhanced.	0.829	2.144

Note: The term 'Alpha' is used to denote Cronbach's Alpha; 'CRA' signifies Composite Reliability (rho_a); 'CRC' serves as an abbreviation for Composite Reliability (rho_c); 'AVE' stands for Average Variance Extracted

ness in managing complex model structures, particularly when multiple mediator variables are present (Hair et al., 2017; Marques et al., 2024). It is suitable for exploratory studies and theory development stages, accommodating small sample sizes and less strict data distribution demands (Hair et al., 2017), providing a flexible and robust analytical framework for this study (Wang & Esperança, 2023).

The analysis began with assessing the reliability and validity of the latent variables through the measurement model, which included tests for internal consistency, convergent validity, and discriminant validity (Henseler et al., 2015). The structural model analysis was conducted to test research hypotheses, which included the examination of the significance of path coefficients, R-squared (R^2) values, and the model's predictive relevance (Q^2) (Hair et al., 2017). The study also employed Importance-Performance Matrix Analysis (IPMA) to investigate further each variable's importance and performance regarding their impact on entrepreneurial performance (Ringle & Sarstedt, 2016). Data analysis was conducted using SmartPLS 4.0 software. The subsequent section will report the specific results of the analysis.

4.4 Common method and non-responsive biases

To mitigate potential common method bias, we randomized the order of variables in the survey design to reduce response bias among participants. Anonymity was maintained in the survey to lessen social desirability bias. The Harman single-factor test was employed to assess the effect of common method bias, with the first factor explaining only 35.60% of the variance, below the critical threshold of 50%, indicating that common method bias is not a severe issue in our research (Podsakoff et al., 2003).

Regarding non-response bias, a targeted sampling strategy was deployed, emphasizing participation's importance in enhancing representativeness and response rate. T-tests comparing early and late respondents were conducted to assess non-response bias (Armstrong & Overton, 1977). No significant differences were found between the two groups across all variables ($p > 0.05$), suggesting negligible non-response bias impact. Thus, measures were taken to minimize both common method bias and non-response bias, ensuring they do not substantively affect the research conclusions.

4.5 Measures to prevent AI washing

To address concerns about potential "AI washing" (Woollacott, 2024) - the practice of making inflated or false claims about AI usage - we implemented several safeguards:

1. We included two screening questions requiring respondents to provide specific examples of how they have used GenAI tools in their entrepreneurial activities: "Have you participated in entrepreneurial activities related to GenAI?", "Which GenAI tools has our team utilized?". Responses lacking concrete details were excluded.
2. We contacted ten respondents for follow-up interviews to help us understand more details, including how to use GAI tools to address language barriers and internet connectivity.
3. We cross-referenced respondents' claimed GenAI applications against their venture's publicly available information where possible. We verified the respondents' feedback by visiting the GAI tool and verified the respondents' specific use of the tool in entrepreneurship through public corporate information. This includes their use of the GAI tool for e-commerce copywriting, poster design, language translation, AI digital human live broadcast, entrepreneurial data analysis, video editing, etc.
4. Our survey included technical questions about GenAI that would be difficult to answer without genuine experience. Our questionnaire allows respondents to withdraw at any time to ensure that the respondents participate voluntarily. By deleting 130 inappropriate samples, such as incomplete answers, identical answers, and too-short answers, we finally obtained 491 valid samples. We try to ensure that the data we obtain is true and reliable.
5. The local survey is conducted anonymously, which means that no identifiable information of the respondents is involved. During the survey, we also informed the respondents that there is no right or wrong answer in the survey and invited them to answer truthfully. Therefore, the respondents can speak freely and truthfully report their actual use of GAI.
6. The questionnaire survey we conducted does not involve any monetary or material rewards. Therefore, the respondents cannot obtain any potential material rewards from this survey. Therefore, the respondents do not need to answer questions like "AI washing" for utilitarian purposes.

These measures help ensure our data reflects authentic GenAI usage rather than exaggerated claims.

5 Results

5.1 Measurement model

Before conducting Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, it was necessary to evaluate the measurement model to confirm the reliability and validity of the scales. The measurement model assessment included checks for internal consistency, convergent validity, and discriminant validity. Internal consistency, often measured by Cronbach's alpha and Composite Reliability (CR), reflects the degree of consistency between items on a scale (Hair et al., 2017; Marques et al., 2024). Convergent validity, typically assessed through the Average Variance Extracted (AVE), indicates the extent to which scale items correlate with their corresponding constructs (Fornell & Larcker, 1981). Discriminant validity, used to appraise the distinctions between different constructs, can be verified using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015).

Data analysis was conducted using SmartPLS 4.0 software. Results (Table 2) demonstrated adequate internal consistency with all constructs' Cronbach's alpha and CR exceeding 0.7 (Hair et al., 2017; Hilkenmeier et al., 2021). Furthermore, all constructs' AVE values surpassed 0.5, signifying sound convergent validity (Fornell & Larcker, 1981). Examination via the Fornell-Larcker criterion and HTMT ratio confirmed that the square root of AVE values for each construct were greater than their inter-construct correlations, and HTMT ratios were below 0.85—indicating good discriminant validity (Table 3) (Henseler et al., 2015).

An additional cross-loadings analysis (Hair et al., 2017; Hilkenmeier et al., 2021) corroborated the validity of the measurement items, showing that loading values for each item were higher on their construct than on others, further supporting the model's convergent and

Table 3 Discriminant validity: Fornell-Larcker Criterion, Heterotrait-Monotrait ratio (HTMT) and cross loadings

Construct	EP	GEC	GHR	GIR	GII	GTR
EP	**0.829**	0.644	0.386	0.358	0.602	0.380
GEC	0.576	**0.843**	0.487	0.384	0.585	0.422
GHR	0.337	0.428	**0.841**	0.231	0.418	0.249
GIR	0.317	0.343	0.201	**0.858**	0.371	0.259
GII	0.534	0.522	0.364	0.327	**0.825**	0.451
GTR	0.330	0.370	0.215	0.226	0.391	**0.826**
Items	**EP**	**GEC**	**GHR**	**GIR**	**GII**	**GTR**
EP1	**0.823**	0.481	0.292	0.273	0.428	0.260
EP2	**0.828**	0.457	0.293	0.252	0.428	0.279
EP3	**0.833**	0.504	0.275	0.237	0.466	0.274
EP4	**0.834**	0.484	0.284	0.283	0.442	0.271
EP5	**0.826**	0.457	0.254	0.268	0.447	0.283
GEC1	0.486	**0.841**	0.362	0.276	0.432	0.278
GEC2	0.459	**0.829**	0.353	0.280	0.449	0.300
GEC3	0.492	**0.825**	0.352	0.266	0.422	0.313
GEC4	0.481	**0.837**	0.367	0.306	0.431	0.316
GEC5	0.507	**0.882**	0.371	0.315	0.465	0.350
GHR1	0.299	0.366	**0.848**	0.160	0.312	0.187
GHR2	0.305	0.354	**0.839**	0.195	0.315	0.191
GHR3	0.284	0.353	**0.836**	0.160	0.314	0.187
GHR4	0.246	0.368	**0.841**	0.162	0.285	0.157
GII1	0.418	0.424	0.315	0.293	**0.822**	0.292
GII2	0.409	0.405	0.295	0.249	**0.819**	0.314
GII3	0.458	0.436	0.309	0.284	**0.830**	0.320
GII4	0.449	0.448	0.289	0.259	**0.828**	0.334
GII5	0.466	0.440	0.296	0.266	**0.829**	0.352
GIR1	0.279	0.291	0.154	**0.846**	0.271	0.190
GIR2	0.296	0.319	0.180	**0.881**	0.296	0.223
GIR3	0.257	0.293	0.182	**0.858**	0.279	0.195
GIR4	0.252	0.270	0.174	**0.846**	0.277	0.166
GTR1	0.270	0.287	0.157	0.149	0.297	**0.828**
GTR2	0.263	0.284	0.159	0.183	0.321	**0.830**
GTR3	0.285	0.341	0.213	0.219	0.346	**0.825**
GTR4	0.270	0.305	0.173	0.191	0.325	**0.821**

Note: The bolded figures represent the square root of the Average Variance Extracted (AVE). The numbers located in the bottom-left corner below the diagonal indicate the outcomes derived from the Fornell-Larcker Criterion, while those in the corresponding position reflect the results of the Heterotrait-Monotrait (HTMT) Ratio analysis

Note: The figures highlighted in bold indicate the loading values corresponding to each item within the construct discriminant validity. The assessment of the measurement model indicates that the scales used were reliable and valid for the subsequent structural model analysis.

5.2 Structural model

The Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to verify the causal relationships within our research model and to ascertain the explanatory power of endogenous variables. The analysis revealed that GenAI internal integration and external collaboration accounted for 33% and 33.5% of the variance in entrepreneurial performance, respectively (Fig. 2). This indicates a robust explanatory capacity of our research model (Hair et al., 2017). Path coefficient outcomes (Fig. 2) showed that GenAI tangible resources had a significant positive impact on both internal integration ($\beta=0.296$, $p<0.001$) and external collaboration ($\beta=0.298$, $p<0.001$), thus supporting hypotheses H1 and H2. Similarly, GenAI intangible resources significantly boosted internal integration ($\beta=0.256$, $p<0.001$) and external collaboration ($\beta=0.200$, $p<0.001$), confirming hypotheses H3 and H4. Additionally, GenAI human resources also showed substantial positive effects on internal integration ($\beta=0.268$, $p<0.001$) and external collaboration ($\beta=0.321$, $p<0.001$), validating hypotheses H5 and H6. Notably, both internal integration ($\beta=0.283$, $p<0.001$) and external collaboration ($\beta=0.399$, $p<0.001$) significantly enhanced entrepreneurial performance, affirming hypotheses H7 and H8. After incorporating university location as a control variable ($\beta=0.066$, $p>0.05$), the revised PLS-SEM analysis results indicate that the relationships between our study variables remain significant, thus supporting our hypotheses. The detailed results are presented in Fig. 2.

The structural model analysis confirmed the congruence of our model and hypotheses, indicating that GenAI resources indirectly influence entrepreneurial performance through internal integration and external collaboration. These findings provide empirical support for a deeper understanding of the intrinsic connection between GenAI resources, the paths of integration, and entrepreneurial performance.

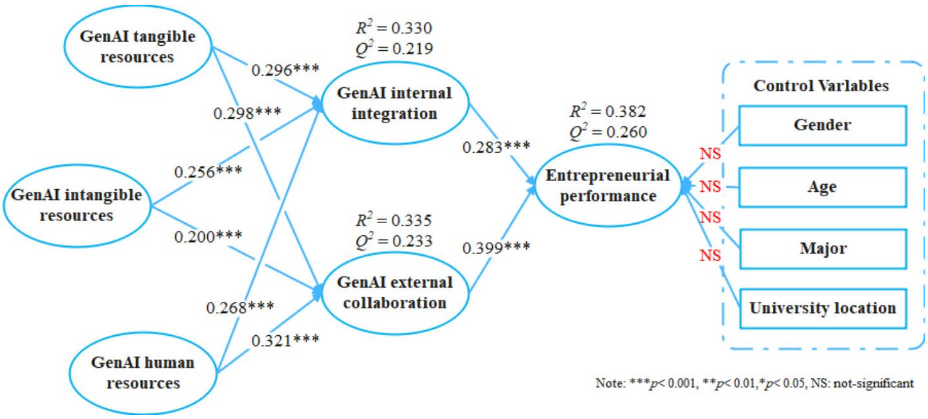

Fig. 2 GenAI & entrepreneurial performance structural model results

Table 4 Indirect effects

Specific indirect effects	Original sample (O)	Standard deviation	*P* values	CI
GTR → GII → EP	0.084	0.017	0.000	(0.054,0.120)
GIR → GII → EP	0.073	0.016	0.000	(0.044,0.107)
GHR → GII → EP	0.076	0.016	0.000	(0.048,0.110)
GHR → GEC → EP	0.128	0.020	0.000	(0.092,0.169)
GTR → GEC → EP	0.119	0.020	0.000	(0.081,0.161)
GIR → GEC → EP	0.080	0.018	0.000	(0.047,0.119)

Table 5 IPMA (entrepreneurial performance)

	Total effect (importance)	Index value (performance)
GenAI external collaboration	0.401	61.741
GenAI human resources	0.205	59.881
GenAI intangible resources	0.153	56.478
GenAI internal integration	0.284	61.072
GenAI tangible resources	0.204	63.697
Mean	0.249	60.574

5.3 Indirect effects analysis

The indirect effects analysis helps examine the indirect influence of independent variables on the dependent variable via mediating variables, revealing the intricate internal mechanisms among variables (Hair et al., 2017). Employing the Bootstrapping method to assess the significance of specific indirect effects, as presented in Table 4, it is evident that GenAI tangible resources, intangible resources, and human resources significantly mediate entrepreneurial performance through internal integration and external collaboration ($p<0.001$). These findings suggest that GenAI resources can further promote entrepreneurial performance by enhancing internal synergy and external cooperation, supporting our responses to research questions RQ1 and RQ2.

5.4 Importance-performance matrix analysis

The Importance-Performance Matrix Analysis (IPMA) offers a multidimensional perspective to evaluate the impact of independent variables on dependent variables, measuring the importance and performance of independent variables (Ringle & Sarstedt, 2016). This study employed the IPMA to further explore the significance and performance of GenAI resources and pathways in affecting entrepreneurial performance.

Results from the IPMA (Table 5; Fig. 3) indicated that GenAI external collaboration has the most substantial influence on entrepreneurial performance, with an importance index of 0.401. This finding underscores GenAI external collaboration as the critical factor in enhancing entrepreneurial performance among all variables examined. Moreover, the performance index of GenAI tangible resources stood at 63.697, the highest among variables, suggesting the pivotal role of optimally allocated tangible resources in the application of GenAI technologies for improving entrepreneurial performance. The importance index for human resources was measured at 0.205, and for internal integration at 0.284, indicat-

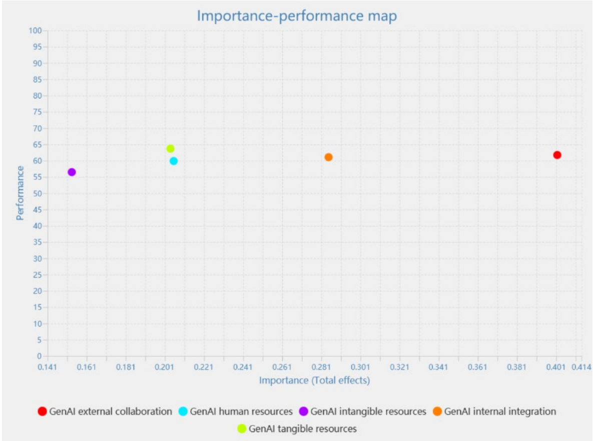

Fig. 3 IPMA (Entrepreneurial performance)

ing that the integration of an enterprise's internal resources and capabilities is decisive in enhancing performance.

6 Discussion

By empirically analyzing the relationships between GenAI resources, internal integration, external collaboration, and entrepreneurial performance, this study enriches the application of Resource-Based Theory (RBT) within the context of emergent technologies. The timing of this research is particularly pertinent. Although GenAI is a relatively new development, its rapid adoption and the preliminary impacts observed in various sectors provide a robust foundation for academic inquiry. Studies like Goel and Nelson (2024) and Mariani and Dwivedi (2024) indicate that the AI revolution is well underway, making it an opportune moment to assess its influence on entrepreneurship. Analyzing survey data from 491 Chinese university student entrepreneurs through Partial Least Squares Structural Equation Modeling (PLS-SEM), we found that GenAI resources significantly improve entrepreneurial performance by fostering internal integration and collaboration, in line with RBT's central premise. That is, enterprises can achieve sustained competitive advantages by configuring and exploiting their unique resources (Barney, 1991; Eisenhardt & Martin, 2000). These findings not only address the current focus in entrepreneurship research regarding the impact of emerging technologies on entrepreneurial performance (Shepherd & Majchrzak, 2022; Obschonka & Audretsch, 2020) but also offer practical insights. Our results highlight the importance of valuing and effectively applying emergent technological resources for enterprises, particularly startups, in a digitized and intelligent environment (Kanbach et al., 2023; Mikalef & Gupta, 2021).

Our study discovers that tangible, intangible, and human GenAI resources significantly positively influence internal integration and external collaboration. This finding not only fills the gap in the literature on GenAI resources influencing entrepreneurial performance but also provides concrete guidance for entrepreneurs to efficiently utilize GenAI. These findings are in accord with the core tenet of RBT, where firms acquire competitive edges through the management and utilization of both internal and external resources (Barney, 1991). It confirms prior research suggestions that resource allocation strategies must consider the integration and application of emergent technological resources in a digitized and intelligent trend (Mikalef & Gupta, 2021; Kanbach et al., 2023).

The results indicate that GenAI internal integration and external collaboration are critical mediating paths boosting entrepreneurial performance, further emphasizing the need for enterprises undergoing digital transformation to focus on resource integration and the construction of external collaboration networks (Gupta & Yang, 2023; Upadhyay et al., 2023). This finding emphasizes the importance of not only accumulating resources but also valuing their effective integration and establishing cooperative networks when leveraging GenAI to propel entrepreneurial activities (Winkler et al., 2023; Kanbach et al., 2023). In a rapidly evolving environment, enterprises must dynamically configure resources to adapt to external changes (Eisenhardt & Martin, 2000).

The Importance-Performance Matrix Analysis (IPMA) explored the influence of each variable on entrepreneurial performance. GenAI external collaboration had the most substantial effect on entrepreneurial performance among all examined variables, highlighting the importance of establishing effective partnerships in the context of rapid GenAI development (Gupta & Yang, 2023; Upadhyay et al., 2023). This finding suggests that entrepreneurs, while using GenAI technologies, should not only focus on internal applications but also actively seek and maintain collaborations with external partners, to better share resources, exchange knowledge, and uncover market opportunities (Kanbach et al., 2023).

The inclusion of university location as a control variable did not significantly alter the direct and indirect effects observed in our original analysis, confirming the robustness of our findings. This study not only theoretically deepens the understanding of how GenAI resources affect entrepreneurial performance through internal integration and external collaboration but also offers valuable guidance for entrepreneurs on effectively leveraging GenAI in practice.

7 Conclusions

This study provides valuable insights into the dynamics of Resource-Based Theory (RBT) within the context of rapidly evolving technologies by investigating the relationships between GenAI resources, internal integration, external collaboration, and entrepreneurial performance. Recognizing the nascent stage of GenAI, we acknowledge that the observed relationships might evolve as the technology matures and diffuses further. Our findings underscore the significance of GenAI resources in enhancing entrepreneurial performance, particularly highlighting the substantial impact of external collaboration among all variables examined. GenAI resources were discovered to significantly elevate entrepreneurial performance by strengthening internal integration and external collaboration. This research not only contributes fresh insights to the theoretical domain but also offers critical implications for entrepreneurial practice. Entrepreneurs utilizing GenAI technologies to advance enterprise development should focus on the accumulation and integration of resources and collaborate with external partners to fully harness the innovative opportunities and competitive advantages brought by GenAI.

7.1 Theoretical implications

This study not only bolsters Resource-Based Theory's applicability in the context of emergent technologies but also provides valuable insights into how enterprises can enhance entrepreneurial performance in the GenAI era through resource integration and external collaboration (Wales et al., 2023). Firstly, our findings reinforce the central tenet of RBT—competitive advantage and performance improvement relies on the effective allocation and utilization of internal resources (Barney, 1991; Eisenhardt & Martin, 2000). In particular, how emergent GenAI resources are utilized becomes a key determinant in entrepreneurial success within a rapidly developing technological landscape (Goel & Nelson, 2024).

Additionally, this research provides new perspectives on dynamic capabilities by revealing the positive impact of GenAI resources on entrepreneurial performance mediated by internal integration and external collaboration (Eisenhardt & Martin, 2000). We delve into not only the influence of GenAI resources but also elucidate the mediating mechanisms of internal coordination and external cooperation (Upadhyay et al., 2023), offering a novel angle for comprehending how firms attain competitive advantages through emerging technological resource allocation (Barney, 1991).

Moreover, by presenting a multidimensional concept of GenAI resources and demonstrating the varying effects, this study guides enterprise planning for GenAI resource investments (Rajaram & Tinguely, 2024). It expands the understanding of AI applications within RBT, underscoring the importance of human resources and organizational capabilities in technological innovation (Mikalef & Gupta, 2021). Our research confirms the viewpoint that in the digital age, companies need to build and use compound resources to achieve innovation and enhance performance (Chen et al., 2022). Our empirical findings not only substantiate GenAI's role in entrepreneurial performance but also probe the underlying mechanisms, providing empirical groundwork for theory development in this domain (Kanbach et al., 2023).

Lastly, our results highlight the critical role of external collaboration in achieving entrepreneurial performance. This discovery offers a fresh perspective on how enterprises can obtain and integrate external resources in an open innovation environment by building effective collaboration networks (Gupta & Yang, 2023; Upadhyay et al., 2023). By demonstrating the mediating role of external collaboration in transforming GenAI resources into entrepreneurial success, our study informs both theoretical discourse and practical strategy on fostering effective partnerships within increasingly complex technological ecosystems.

7.2 Practical implications

Entrepreneurs should prioritize the aggregation and strategic deployment of GenAI tangible resources, as their effective allocation is crucial for innovation and performance enhancement (Colombelli et al., 2023; Mariani & Dwivedi, 2024). Our research emphasizes the fundamental role of tangible assets, such as hardware, data, and software tools, in applying GenAI. Enterprises need to commit adequate resources to establish and sustain these tangible assets, providing a solid foundation for GenAI's extensive application. By valuing the accumulation and management of GenAI resources, cultivating supportive intangible resources, strengthening internal and external collaboration, and focusing on human resource development, entrepreneurs can capitalize on the opportunities GenAI affords to achieve entrepreneurial success.

The cultivation of intangible resources is equally pivotal. A culture of innovation, strategic planning, and recognition of GenAI's importance not only facilitates internal integration and collaboration but also directly relates to the enhancement of entrepreneurial performance. The nurturing of an innovative culture and strategic orientation are critical elements for gaining competitive advantages within the Resource-Based Theory framework (Chen et al., 2022). Entrepreneurs should intensify their team's understanding and practical application skills of GenAI through training, learning, and interaction, thus creating an organizational culture that supports innovation.

Strengthening internal integration and external collaboration is vital for boosting entrepreneurial performance. Our study's findings indicate that these are essential mediating pathways through which GenAI resources transform into improved entrepreneurial performance. External collaboration plays a key role in the innovation of business models (Kanbach et al., 2023). Entrepreneurs should establish effective communication mechanisms and collaboration platforms to promote knowledge sharing and resource integration, as well as actively explore cooperation opportunities with external partners to gain additional support and resources. Entrepreneurs need to consider how to integrate GenAI technology effectively with existing business processes and systems to deepen its application across various business domains, thereby improving operational efficiency and innovation capabilities. Entrepreneurs should expand their GenAI collaborative networks, working closely with industry peers to enable rapid innovation cycles of GenAI technology, application scenarios, and business models (Gupta & Yang, 2023). Expanding GenAI external networks allows entrepreneurs to attract more external support, stay abreast of technological trends, and establish differentiated competitive advantages (Upadhyay et al., 2023).

The development and application of human resources are critical. Training and elevating GenAI human resources are essential for enhancing internal integration ability and bolstering external cooperation. Human resources play a central role in technological innovation and organizational performance improvement. Entrepreneurs should emphasize the attraction and growth of talent to heighten the team's operational capacity and innovative application proficiency in GenAI. Entrepreneurs should emphasize the attraction and growth of talent to heighten the team's operational capacity and innovative application proficiency in GenAI, including providing language training where necessary to maximize the utility of international GenAI resources and platforms.

7.3 Limitations and future research

While this study provides new insights into the mechanisms through which GenAI resources boost entrepreneurial performance, it has limitations. Analyzing a sample composed predominantly of Chinese university student entrepreneurs may restrict the generalizability of our conclusions. Future research could incorporate cross-national and cross-cultural samples to substantiate the robustness of our findings. Utilizing cross-sectional data impedes capturing the dynamic nature of the relationship between GenAI resources and entrepreneurial performance. We strongly recommend longitudinal study designs for future research, ideally conducted after a year or two of widespread GenAI adoption. This approach would allow researchers to explore the enduring effects of GenAI resource deployment and utilization, capture the technology's stabilization process, and provide more robust insights into its long-term impact on entrepreneurial performance. This study concentrates on the impact of GenAI resources on entrepreneurial performance without fully considering potential influences from external environmental factors, such as market dynamics and industry characteristics. Subsequent studies might integrate these external variables to construct a more comprehensive theoretical framework. Considering the rapid advancement and expanding application areas of GenAI technology, future investigations should also pay attention to resource allocation strategies in different GenAI application contexts and their effects on entrepreneurial performance, as well as how improvements in GenAI technology affect entrepreneurs' resource integration capabilities and external collaboration models. Additionally, this study did not explicitly assess respondents' English language proficiency, which may influence their ability to fully utilize certain GenAI tools and resources that are predominantly in English. Future research should consider including English language proficiency as a control variable to account for its potential moderating effect on the relationships examined in this study. While we implemented measures to mitigate "AI washing", we acknowledge the possibility that some respondents may have overstated their GenAI usage. Future research could employ more rigorous verification methods, such as direct observation or access to usage logs of GenAI tools, to further validate self-reported data.

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Data availability The datasets used or analysed during the current study are available from the author on reasonable request.

Declarations

Ethical approval Not applicable.

Conflict of interest The authors have no conflicts of interest to declare.

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