

Article

How Dynamic Capabilities and Ambidextrous Learning Shape SME Innovation Performance: The Moderating Role of Exploratory and Exploitative Learning

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Abstract

This study examines the differential effects of three dimensions of dynamic capabilities on innovation performance and investigates how ambidextrous learning (exploratory and exploitative learning) moderates these relationships. Drawing on survey data from 299 Chinese enterprises, we employ hierarchical regression analysis with interaction terms to test the proposed hypotheses. The results reveal that all three capability dimensions significantly enhance innovation performance, with innovative capacity exerting the strongest effect. Both exploratory and exploitative learning positively moderate the capability–performance relationships, though their effects vary across capability dimensions: exploitative learning more strongly reinforces the effect of absorptive capacity, while exploratory learning more effectively amplifies the influence of innovative capacity. These findings contribute to the dynamic capabilities literature by revealing the heterogeneous performance implications of distinct capability dimensions and demonstrating how different learning modes serve as boundary conditions that shape capability effectiveness.

Keywords: exploratory learning; exploitative learning; dynamic capability; innovation performance

1. Introduction

China is undergoing a profound period of economic restructuring, marked by heightened uncertainty, accelerating digitalization, and increasing environmental complexity. In such a volatile context, traditional competitive advantages are rapidly eroding, while emerging opportunities and challenges coexist and intensify competitive pressures in the marketplace [1]. To ensure sustainable development under these dynamic conditions, enterprises must increasingly rely on innovation-driven strategies. However, as market turbulence rises and competitive boundaries shift, static organizational capabilities are no longer sufficient for firms to maintain competitiveness or respond effectively to unpredictable environmental changes [2].

Dynamic capabilities have therefore emerged as a critical mechanism enabling firms to sense, seize, and reconfigure resources in response to environmental shifts. By integrating internal and external knowledge, restructuring organizational routines, and facilitating timely resource orchestration, dynamic capabilities provide firms with the adaptive

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capacity needed to respond to competitive challenges and capture emerging opportunities [3]. For small and medium-sized enterprises (SMEs), which typically face severe resource constraints and limited managerial expertise, developing dynamic capabilities is particularly crucial for sustaining innovation and navigating digital transformation [4]. Yet many SMEs struggle to fully leverage capability development or embed adaptive learning processes into their innovation activities, raising an important question: how do capability configurations and organizational learning modes interact to enhance innovation performance?

Despite extensive research on dynamic capabilities, three significant gaps remain in the existing literature. First, most studies conceptualize dynamic capabilities as a unified construct, providing limited insight into how individual dimensions—such as absorptive, integrative, and innovative capacities—contribute differentially to innovation performance [5]. This aggregated approach obscures potentially important variations in how specific capability dimensions drive innovation outcomes, constraining both theoretical advancement and practical guidance for targeted capability development. Understanding these differential effects is essential for SMEs that must strategically allocate limited resources to capability building efforts.

Second, while the capability-performance relationship has been examined under various boundary conditions, including environmental dynamism and competitive intensity [6], the role of organizational learning processes in shaping this relationship remains underexplored. Innovation is inherently a knowledge-intensive and cumulative process, and ambidextrous learning—comprising exploratory and exploitative learning—provides critical pathways through which firms renew knowledge, deepen expertise, and enhance resource deployment [7]. However, empirical studies that explicitly examine how different learning modes moderate the effects of specific capability dimensions on innovation performance are notably scarce.

Third, empirical research on dynamic capabilities and innovation performance has been conducted predominantly in Western contexts, with relatively few studies examining these relationships in emerging markets [8]. The institutional, cultural, and competitive characteristics of the Chinese market may influence both the development of dynamic capabilities and their performance implications. Given that Chinese SMEs operate under distinctive conditions—including rapid technological change, intense domestic competition, and evolving regulatory frameworks—context-specific investigation is warranted to assess the generalizability of existing theoretical frameworks.

To address these gaps, this study develops and empirically tests a theoretical framework that examines the differential effects of three dynamic capability dimensions on SME innovation performance. Furthermore, we investigate how ambidextrous learning, comprising exploratory and exploitative learning, moderates these capability-performance relationships. Drawing on survey data from 299 Chinese enterprises, we employ hierarchical regression analysis to test the proposed hypotheses.

This study contributes to literature in three primary ways. First, by disaggregating dynamic capabilities into absorptive, integrative, and innovative dimensions, we provide a more nuanced understanding of how specific capability types drive innovation performance, revealing that innovative capacity exerts the strongest effect while absorptive and integrative capacities also play significant roles. Second, by demonstrating that both exploratory and exploitative learning positively moderate the capability-performance relationships, we illuminate the boundary conditions under which dynamic capabilities most effectively translate into innovation outcomes, showing that learning mechanisms function as amplifiers within the capability system. Third, by conducting empirical investigation in the Chinese SME context, we extend the generalizability of capability-learning

frameworks to emerging market settings and offer practical insights for enterprises navigating environmental turbulence and digital transformation.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on dynamic capabilities and ambidextrous learning. Section 3 develops the theoretical framework and research hypotheses. Section 4 describes the research methodology, including data collection and measurement. Section 5 presents empirical results. Section 6 discusses the findings and their theoretical implications. Section 7 concludes with a summary of contributions, managerial implications, limitations, and directions for future research.

2. Literature Review

2.1. Dynamic Capabilities Theory

The concept of dynamic capabilities emerged as a theoretical response to the limitations of the resource-based view (RBV) in explaining how firms achieve sustainable competitive advantage in rapidly changing environments. While the RBV emphasizes the strategic importance of valuable, rare, inimitable, and non-substitutable resources, it offers limited insight into how firms can continuously renew and reconfigure their resource base to adapt to environmental shifts [9]. Dynamic capabilities theory addresses this gap by focusing on the organizational processes through which firms sense opportunities, seize them through resource mobilization, and transform their resource configurations to maintain competitiveness [10].

Teece, Pisano, and Shuen [11] introduced the foundational definition of dynamic capabilities as “the firm’s ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments.” Subsequently, Eisenhardt and Martin [12] offered a complementary process-oriented perspective, defining dynamic capabilities as organizational and strategic routines by which firms achieve new resource configurations. Teece [3] further refined his framework by identifying three primary clusters: sensing—the capacity to scan and explore opportunities; seizing—the ability to mobilize resources to capture value; and transforming—the capacity to continuously renew organizational assets and structures.

Despite broad agreement on the importance of dynamic capabilities, scholars have proposed diverse dimensional structures. From a knowledge-based perspective, Zahra and George [13] distinguished between potential and realized absorptive capacity. Wang and Ahmed [14] proposed adaptive, absorptive, and innovative capacities from a behavioral perspective. This diversity reflects the multifaceted nature of dynamic capabilities and the context-dependent processes through which they operate. Absorptive capacity enables firms to identify valuable external knowledge, integrate it with existing stocks, and apply it to new product development [15]. Integrative capacity emphasizes coordination and synthesis of diverse knowledge sources, technologies, and resources [16]. Innovative capacity captures the firm’s ability to develop new products, services, and processes by transforming knowledge inputs into commercially viable outputs [17].

The application of dynamic capabilities theory to SMEs presents both opportunities and challenges. SMEs often exhibit greater organizational flexibility and shorter decision-making cycles, potentially enabling faster capability reconfiguration [18]. However, they typically face severe resource constraints and limited access to external knowledge networks [4]. Despite growing scholarly interest, empirical research on how different dimensions of dynamic capabilities contribute differentially to SME innovation performance remains fragmented, with most studies treating dynamic capabilities as a unitary construct [5]. This study therefore adopts a three-dimensional structure comprising absorptive, integrative, and innovative capacities to capture the sequential processes of knowledge acquisition, resource coordination, and value creation.

2.2. A Dynamic Capabilities Perspective on Firm Innovation

A substantial body of research supports the positive relationship between dynamic capabilities and innovation performance. Dynamic capabilities enable firms to identify emerging opportunities, mobilize resources for innovation activities, and overcome organizational inertia [19]. By facilitating continuous resource reconfiguration, dynamic capabilities help firms reduce uncertainty in the innovation process and accelerate new product development [20].

Empirical studies have documented positive associations between various capability dimensions and innovation outcomes. Absorptive capacity enhances innovation performance by enabling firms to identify, assimilate, and apply external knowledge to new product development [21]. Integrative capacity facilitates cross-functional collaboration and knowledge synthesis essential for innovation activities requiring diverse expertise [22]. Innovative capacity represents the most proximate driver of innovation performance, directly influencing the firm's capacity to generate and commercialize new products and services [23].

While the direct effect perspective has received substantial support, alternative research streams emphasize indirect effects through mediating mechanisms or boundary conditions [24]. The contingency perspective suggests that the capability-performance relationship varies depending on factors such as environmental dynamism and competitive intensity [6]. Despite significant progress, gaps remain in understanding how individual capability dimensions contribute differentially to innovation outcomes and what mechanisms shape these relationships. The role of organizational learning processes in moderating capability-performance relationships has received insufficient attention, and empirical research in emerging market contexts, particularly China, remains limited [8].

2.3. Ambidextrous Learning Theory

The concept of organizational ambidexterity originates from March's [7] seminal distinction between exploration and exploitation. Exploration involves search, variation, risk-taking, and experimentation, while exploitation encompasses refinement, efficiency, selection, and implementation. These learning modes represent fundamentally different approaches to organizational adaptation, with exploration oriented toward discovering new possibilities and exploitation focused on refining existing competencies. March's framework highlights an inherent tension: organizations focusing exclusively on exploration may suffer from excessive experimentation, while those emphasizing exploitation may achieve short-term efficiency but risk obsolescence [25].

Exploratory learning represents efforts to acquire new knowledge and pursue emerging opportunities through search activities extending beyond current knowledge domains [26]. Organizations engaged in exploratory learning actively seek knowledge from diverse external sources, enabling identification of emerging trends and opportunities for value creation [27]. Research shows that exploratory learning enhances organizational flexibility and facilitates breakthrough innovations, though it entails significant costs and uncertain returns [28].

Exploitative learning involves refinement and deepening of existing knowledge and capabilities, focusing on improving efficiency and productivity within established domains [29]. Mechanisms include systematic codification of accumulated knowledge and incremental improvement of existing products and processes [30]. Firms that effectively exploit existing knowledge achieve lower costs, higher quality, and faster response times, though excessive emphasis may create competency traps limiting adaptability [31].

The relationship between ambidextrous learning and dynamic capabilities represents an emerging area of inquiry. Learning processes provide raw material for capability development by enabling knowledge acquisition and transformation [32]. Some studies

position learning as antecedents to capability development, while others suggest capabilities enable more effective learning [33]. A third perspective, informing this study, conceptualizes ambidextrous learning as a boundary condition shaping the capability-performance relationship [34]. From this view, exploratory learning may enhance capability effects by introducing new knowledge that refreshes existing capabilities, while exploitative learning may strengthen these relationships by improving efficiency of capability deployment. However, empirical research examining ambidextrous learning as a moderating mechanism remains scarce, particularly in Chinese contexts, representing a significant gap this study aims to address.

3. Theoretical Framework and Research Hypotheses

3.1. *Dynamic Capabilities and Innovation Performance*

Building on the literature reviewed above, this study examines how the three dimensions of dynamic capabilities—absorptive, integrative, and innovative capacities—influence enterprise innovation performance. Dynamic capabilities theory posits that firms possessing the ability to sense environmental changes, reconfigure resources, and transform organizational routines are better positioned to achieve superior innovation outcomes [10]. In rapidly changing environments, static resource endowments are insufficient for sustaining competitive advantage; rather, the capacity to continuously adapt and renew capabilities becomes paramount [12].

Absorptive capacity represents the firm's potential to acquire, assimilate, and apply external knowledge for commercial purposes [15]. In the innovation process, merely acquiring external knowledge does not directly benefit firms; rather, the ability to recognize the value of external information, internalize it, and adapt it to internal processes is critical for generating new knowledge and innovative outputs [13]. Enterprises that actively acquire valuable external information can leverage their absorptive capacity to enhance innovation by internalizing external knowledge and fostering new knowledge creation. External information and knowledge significantly support the development of new products and services, as firms process heterogeneous inputs through detailed interpretation and transformation [21]. Unfamiliar or context-specific information is digested, redundant knowledge is eliminated, and newly processed knowledge is shared internally, improving organizational knowledge flow and accumulation. This enhanced knowledge base provides the foundation for novel product development and process improvements, thereby promoting innovation performance. Therefore, we propose:

H1. *Absorptive capacity is positively associated with enterprise innovation performance.*

Integrative capacity represents a higher-order organizational competence that enables systematic coordination, configuration, and reconstruction of internal and external resources [16]. Innovation activities typically require the combination of cross-disciplinary knowledge, diverse expertise, and heterogeneous resources. Effective coordination and integration of such knowledge become essential for successful innovation outcomes [35]. When enterprises integrate accumulated technological knowledge and actively coordinate internal and external resources, their technological knowledge becomes more diversified, systematic, and structured. This integration process improves both the breadth and depth of knowledge acquisition, facilitates cross-functional collaboration, and accelerates new product development [36]. Moreover, integrative capacity enables firms to align innovation activities with strategic objectives and optimize resource allocation across innovation projects, thereby enhancing innovation performance. Therefore, we propose:

H2. Integrative capacity is positively associated with enterprise innovation performance.

Innovative capacity constitutes a primary determinant of differences in firms' innovation performance [17]. This capability captures the firm's ability to develop new products, services, processes, or business models by leveraging accumulated knowledge and resources. By integrating, utilizing, and exploring potential resources, enterprises can combine accumulated internal and external knowledge and leverage R&D capacity to achieve technological breakthroughs, reinvent existing knowledge, develop novel products, and introduce new services [37]. The greater the firm's ability to acquire new knowledge and technology, the stronger its capability to transform knowledge into innovative products and services, enhance product quality, expand market share, and improve innovation performance. Firms with strong innovative capacities can more effectively translate technological opportunities into market offerings and sustain competitive differentiation through continuous innovation [23]. Therefore, we propose:

H3. Innovative capacity is positively associated with enterprise innovation performance.

3.2. The Moderating Role of Ambidextrous Learning

While dynamic capabilities provide the foundation for innovation activities, organizational learning processes determine how effectively firms can leverage their capability base to achieve desired outcomes [34]. Ambidextrous learning serves as a critical pathway for knowledge expansion, accumulation, and renewal [7]. Drawing on organizational learning theory, we argue that both learning modes function as boundary conditions that shape the relationship between dynamic capabilities and innovation performance.

The theoretical rationale for examining learning as a moderator rests on two key arguments. First, learning processes provide the raw material for capability deployment by enabling the acquisition, assimilation, and transformation of knowledge resources [32]. The effectiveness of dynamic capabilities in driving innovation outcomes depends substantially on the quality and nature of knowledge inputs that learning processes generate. Second, learning orientations shape how firms interpret and respond to environmental signals, influencing the direction and efficiency of capability deployment [33]. Firms with different learning orientations may leverage similar capabilities in distinct ways, resulting in differential performance outcomes.

3.2.1. The Moderating Role of Exploratory Learning

Exploratory learning involves search, variation, experimentation, and the pursuit of new knowledge in emerging domains [7]. Under an exploratory learning orientation, firms tend to acquire novel professional knowledge and skills from both internal and external sources, combining new and existing knowledge to construct innovative knowledge systems that support innovative activities.

Regarding absorptive capacity, firms with strong absorptive capacities can effectively assimilate new knowledge and technologies, thereby expanding the breadth and depth of their knowledge base [38]. When combined with exploratory learning, these firms are more likely to explore diverse resource channels and acquire multi-domain knowledge and technical resources. The continuous inflow of frontier knowledge, coupled with effective internal absorption, transformation, and sharing, stimulates innovative thinking and accelerates the introduction of new products and services. Exploratory learning amplifies the effect of absorptive capacity by directing attention toward novel external knowledge sources and facilitating the integration of diverse knowledge elements. Therefore, we propose:

H4a. *Exploratory learning positively moderates the relationship between absorptive capacity and enterprise innovation performance.*

Regarding integrative capacity, when external knowledge and technology diffuse internally and are refined through organizational routines, firms can restructure operational processes, coordinate and match resources, and balance existing competencies [22]. Exploratory learning enhances environmental sensitivity and enables firms to leverage synergistic effects among diverse resources, stimulating innovation activities and securing first-mover advantages in emerging markets. Feedback from market changes and the exploration of newly acquired knowledge facilitate rapid transformation of insights into market-oriented products or services [39]. Exploratory learning strengthens integrative capacity's effect by providing diverse knowledge inputs that can be recombined and coordinated in novel ways. Therefore, we propose:

H4b. *Exploratory learning positively moderates the relationship between integrative capacity and enterprise innovation performance.*

Regarding innovative capacity, when institutional, production, or managerial barriers arise during knowledge and technology transformation, firms with strong innovative capacities can overcome such constraints [40]. Exploratory learning supports this process by enabling firms to apply new knowledge in operations and generate creative ideas aligned with market needs. By continuously converting new technologies and ideas into innovative products and services, firms can expand into new markets and secure competitive advantages [41]. The combination of innovative capacity and exploratory learning creates a powerful mechanism for breakthrough innovation, as firms simultaneously possess the capacity to transform knowledge and the orientation to pursue novel opportunities. Therefore, we propose:

H4c. *Exploratory learning positively moderates the relationship between innovative capacity and enterprise innovation performance.*

3.2.2. The Moderating Role of Exploitative Learning

Exploitative learning involves the refinement, selection, implementation, and reuse of existing knowledge bases, aiming to deepen understanding and improve established practices [29]. Under an exploitative learning orientation, firms deepen their understanding of existing knowledge, technologies, and paradigms, thereby increasing the frequency and efficiency of knowledge application.

Regarding absorptive capacity, exploitative learning enhances the firm's capacity to refine and enrich existing knowledge reserves by embedding learning into daily operations [30]. Firms with strong absorptive capacities can better digest and upgrade specialized knowledge and skills, transforming accumulated knowledge into creative applications. By embedding learning into daily operations—such as R&D, production, and marketing, firms can shorten feedback cycles, improve operational efficiency, and enhance precision in product development, thereby accelerating the introduction of new products and services [42]. Exploitative learning amplifies absorptive capacity's effect by improving the efficiency of knowledge utilization and reducing uncertainty in the innovation process. Therefore, we propose:

H5a. *Exploitative learning positively moderates the relationship between absorptive capacity and enterprise innovation performance.*

Regarding integrative capacity, when deeply mined knowledge is reorganized internally, optimization occurs across product innovation, production processes, and operational practices [43]. Exploitative learning provides direct, stable, and short-term solutions, minimizing uncertainties in R&D and production and thereby accelerating new product development. The combination of integrative capacity and exploitative learning enables firms to achieve efficient coordination of existing knowledge elements, reducing redundancy and improving the speed of innovation implementation [28]. Therefore, we propose:

H5b. *Exploitative learning positively moderates the relationship between integrative capacity and enterprise innovation performance.*

Regarding innovative capacity, after transformation and internal communication, deeply mined knowledge promotes knowledge flow and the emergence of innovative ideas [44]. Exploitative learning enables firms to draw on existing experience and technology, responding flexibly to dynamic environments in R&D and production. This orientation facilitates achieving stable returns, immediate effects, and reduced project timelines, thereby realizing innovation gains within shorter periods [45]. The combination of innovative capacity and exploitative learning creates efficiency in the innovation process, as firms can rapidly deploy existing knowledge to generate incremental innovations. Therefore, we propose:

H5c. *Exploitative learning positively moderates the relationship between innovative capacity and enterprise innovation performance.*

Based on the above analysis, the theoretical framework of this study is illustrated in Figure 1.

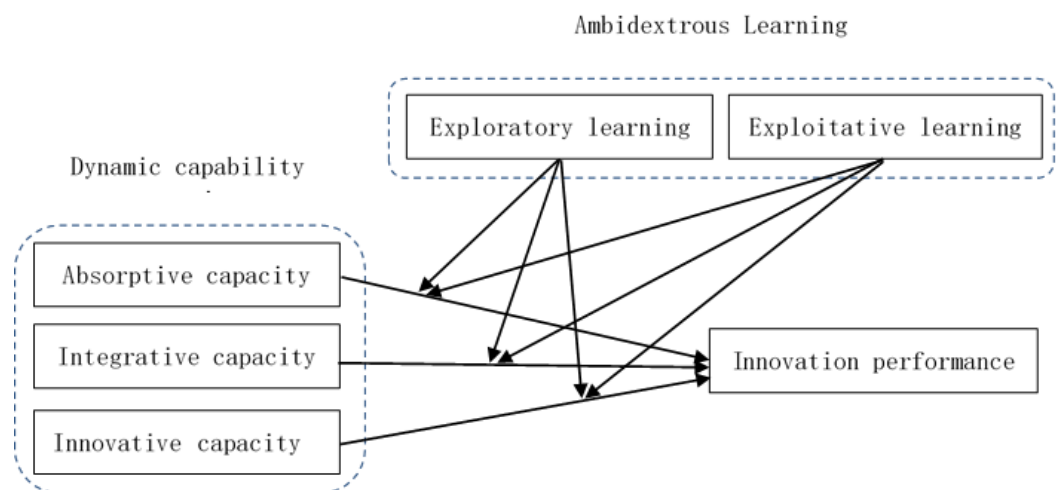


Figure 1. Conceptual Model. Note: Solid arrows (→) from dynamic capability dimensions to innovation performance represent the hypothesized direct effects (H1: absorptive capacity; H2: integrative capacity; H3: innovative capacity). The dashed box labeled "Ambidextrous Learning" indicates that exploratory learning (H4a–H4c) and exploitative learning (H5a–H5c) moderate these direct relationships.

4. Research Design

4.1. Data Sources and Sample Description

This study employed a questionnaire survey to collect primary data. The measurement scales were adapted from established international instruments and refined to align with the specific context of Chinese enterprises. The survey was conducted in two stages.

In the first stage, a semi-structured pilot questionnaire was developed by integrating the attributes of dynamic capabilities and descriptions reflecting innovation performance. Six enterprises were selected for a pre-survey conducted in March 2019, and all questionnaires were retrieved by April 2019. Based on the pre-survey results, questionnaire items were refined—key terms were ranked by importance, and revisions were made regarding technical terminology, scientific expression, format, and translation accuracy. A finalized version of the questionnaire was subsequently developed. All variables were measured using a seven-point Likert scale, ranging from 1 (“strongly disagree”) to 7 (“strongly agree”).

The formal survey was administered in June 2019 using a combination of on-site and email distribution methods. Sample enterprises were located in Beijing, Shanghai, Shenzhen, Xi'an, Wuhan, Chengdu, and Harbin—major economic centers representing diverse regional contexts across China. The respondents were middle- and senior-level managers who possessed comprehensive knowledge of their enterprise's operations and could influence decision-making processes. This respondent selection strategy ensures that the collected data accurately reflect organizational-level constructs such as dynamic capabilities and learning orientations.

A total of 450 questionnaires were distributed, and 334 were retrieved, yielding an overall response rate of 74.22%. After data screening, 35 questionnaires were excluded due to missing data (more than 10% incomplete items), patterned responses (identical answers across all items), or apparent logical inconsistencies, resulting in 299 valid responses with an effective response rate of 66.44%.

Following the classification standards issued by the Ministry of Industry and Information Technology of China, small and medium-sized enterprises (SMEs) are defined based on industry-specific criteria involving employee count, operating revenue, and total assets. For the manufacturing sector, SMEs are defined as enterprises with fewer than 1000 employees or operating revenue below 400 million yuan. For the service sector, SMEs are defined as enterprises with fewer than 300 employees or operating revenue below 100 million yuan. It is important to note that in the Chinese context, ownership type (state-owned, private, foreign-invested) is independent of enterprise size classification—state-owned enterprises can qualify as SMEs if they meet the specified employee and revenue thresholds. While our sample includes enterprises of varying ownership types, all sampled firms meet the SME classification criteria based on employee count and revenue thresholds as verified during data collection. The inclusion of diverse ownership types (state-owned, private, joint ventures) enhances the generalizability of our findings across the broader SME population in China.

Although the empirical data were collected in 2019, the core mechanisms linking dynamic capabilities, organizational learning, and innovation performance capture enduring organizational processes that remain highly relevant in today's increasingly competitive and digitalized business environment.

Table 1 presents the descriptive statistics of sample characteristics. Among the surveyed enterprises, those established for over 20 years accounted for the largest proportion (35.12%), followed by those established for 10–20 years (28.76%), while enterprises founded within one year represented the smallest share (3.01%). This distribution indicates that our sample primarily comprises established SMEs with substantial operational

experience. In terms of asset scale, enterprises with assets exceeding 30 million yuan made up the majority (57.86%). Regarding ownership type, private enterprises represented the largest share (59.87%), followed by state-owned enterprises (29.09%), and Sino-foreign joint ventures accounted for 3.01% of the total sample. This ownership distribution is broadly consistent with the overall structure of Chinese SMEs, where private enterprises constitute the dominant form.

Table 1. Descriptive Statistics of Sample Characteristics ($N = 299$).

Sample Characteristic	Measurement Indicator	Frequency	Percentage (%)
Enterprise Years	1 year or less	9	3.01
	1–5 years	42	14.05
	5–10 years	57	19.06
	10–20 years	86	28.76
	Over 20 years	105	35.12
Enterprise asset scale	Below 1 million	18	6.02
	1–3 million	39	13.04
	3–5 million	12	4.01
	5–10 million	27	9.03
	10–30 million	30	10.03
	over 30 million	173	57.86
Enterprise Type	State-Owned Enterprises(SOEs)	87	29.09
	Private Enterprises	179	59.87
	Sino-Foreign Joint Ventures	9	3.01
	Wholly Foreign-Owned Enterprises	12	4.01
	Others	12	4.01

4.2. Scale Design

Measurement of Independent Variables: In defining the dimensions of dynamic capability, this study follows the perspectives of Wang, Jian Zhaoyuan, and Teece [3,46,47], dividing dynamic capability into three core dimensions: absorptive capacity, integrative capacity, and innovative capacity. Each of these three dimensions is measured using four items, respectively.

Measurement of Dependent Variable: Innovation performance was measured using the scale developed by Ritter [48], which consists of four items assessing a firm's innovation outcomes.

Measurement of Moderating Variables: Based on the studies of March, Atuahene-Gima, and Chung [49,50], ambidextrous learning was divided into two dimensions: exploratory learning and exploitative learning. The exploratory learning dimension includes five items, while exploitative learning includes seven items. Detailed measurement items are presented in Table 2.

Table 2. Variable Items ($N = 299$).

Variables	Measurement Items	Reference Scholar
Independent Variable	(1) Our enterprise can rapidly identify external new knowledge conducive to our development based on market trends.	Cohen, Zahra & George [13,15]
	(2) Our enterprise frequently interacts with other companies in the industry to acquire new knowledge and technologies.	

		(3) Our enterprise frequently shares experiences related to knowledge acquisition and creation internally to effectively apply knowledge. (4) Our enterprise can assimilate external new knowledge and technologies into the organization to meet evolving market demands.	
	Integrative capacity	(1) Our enterprise can leverage and adapt relevant new technological information in response to shifts in the market environment. (2) Our enterprise is capable of rapidly integrating new information and knowledge, disseminating it throughout the enterprise. (3) Our enterprise can apply rapidly integrate new information and knowledge to the development of new products or new markets. (4) Our enterprise is capable of rapidly reconfiguring internal resources and fostering cross-departmental collaboration to achieve strategic objectives.	Pavlou & El Sawy [51]
	Innovative capacity	(1) Our enterprise can rapidly incorporate market feedback into the development process of new products or services. (2) Our enterprise frequently experiments with novel ideas or approaches for the development of new products and services. (3) Our enterprise is capable of swiftly applying knowledge from diverse sources to the development of new products and services. (4) Our enterprise proactively seeks new profit growth opportunities through its products and services.	Lawson & Samson [17]
Dependent variable	Innovation performance	(1) Compared to our primary competitors, our enterprise introduces a greater number of innovative production and operational methods. (2) Compared to our primary competitors, our enterprise is often the first in the industry to launch new products and services. (3) Compared to our primary competitors, the innovation and improvement in our products achieve superior market acceptance. (4) Compared to our primary competitors, our enterprise possesses industry-leading technological processes and operational procedures.	Ritter [48]
Moderating variable	Exploratory learning	(1) Our enterprise places high value on acquiring new technologies and skills from the market. (2) Our enterprise emphasizes learning development skills for new products/services and industry processes. (3) Our enterprise tends to intensify the learning of new technologies in domains where we lack experience. (4) Our enterprise prefers to acquire completely new technologies and skills through the collection and synthesis of new information to facilitate application.	Chung, Atuahene-Gima [49,50]

	(5) Our enterprise focuses on learning new technologies and skills through multiple channels and diverse fields.	
Exploitative learning	(1) Our enterprise emphasizes consolidating existing knowledge and skills to support our current products and services.	
	(2) Our enterprise places a high priority on refining the skills associated with our established product development processes.	
	(3) Our enterprise tends to allocate available resources to mature technologies and skills in order to enhance productivity.	Chung, Atuahene-Gima [49,50]
	(4) Our enterprise focuses on upgrading existing technologies and skills to improve the efficiency of ongoing innovation activities.	
	(5) Our enterprise tends to apply information-gathering methods to renew the knowledge base of our existing products and services.	
	(6) Our enterprise prioritizes finding solutions to problems that arise during the development of products and services.	
	(7) Our enterprise focuses on seeking ideas and information that ensure the stability and optimization of our production capabilities.	

4.3. Analytical Strategy

To examine the relationships among dynamic capabilities, ambidextrous learning, and innovation performance, this study employed hierarchical regression analysis. This approach allows for a assessment of incremental explanatory power by introducing variables in a theoretically informed sequence. Control variables were entered first to establish a baseline model. The three dimensions of dynamic capabilities (absorptive, integrative, and innovative capacities) were then added to test their main effects on innovation performance. Subsequently, exploratory learning and exploitative learning were introduced to examine their direct effects. Finally, interaction terms between dynamic capability dimensions and learning modes were included to assess the proposed moderating effects.

This study adopts hierarchical regression analysis based on several methodological considerations. First, the primary objective of research is to examine moderating effects—specifically, how exploratory and exploitative learning shape the relationships between different dimensions of dynamic capabilities and innovation performance. Hierarchical regression with interaction terms provides a well-established and interpretable approach for testing such conditional relationships and allows for a clear assessment of the incremental explanatory power (ΔR^2) associated with moderating effects [52,53]. In addition, hierarchical regression facilitates the sequential introduction of variables in line with the theoretical framework, enabling transparent evaluation of the marginal contribution of each block of variables to innovation performance. Finally, this analytical approach is widely adopted in the dynamic capabilities and organizational learning literature for testing moderation hypotheses (e.g., [6,28,34]) and thus aligns with established methodological practices in this research domain.

Prior to constructing the interaction terms, all continuous independent and moderating variables were mean centered following the procedure recommended by Aiken and West [52]. Mean-centering helps reduce potential multicollinearity between interaction

terms and their constituent variables and facilitates the interpretation of regression coefficients.

Given that all variables were collected from single respondents at a single point in time, common method bias (CMB) may represent a potential concern. To address this issue, both procedural and statistical remedies were adopted. Procedurally, respondents were assured of anonymity and confidentiality, measurement items were separated across different sections of the questionnaire, and different scale formats were used where appropriate.

Statistically, Harman's single-factor test was employed to assess the potential impact of common method bias. All 28 measurement items were entered into an exploratory factor analysis using principal component extraction without rotation. The results revealed that the first factor explained 45.96% of the total variance, which is below the 50% threshold criterion [54]. Additionally, five factors emerged with eigenvalues exceeding 1.0, collectively accounting for 75.82% of the total variance. These results suggest that common method bias is not a serious concern in this study.

5. Data Analysis

5.1. Reliability and Validity Tests

To ensure the scientific rigor and reliability of the research data, both reliability and validity analyses were conducted on the questionnaire. Using orthogonal rotation with the maximum variance method (varimax rotation), all variables in the questionnaire were examined separately. The specific results are shown in Table 3, and the analysis findings are summarized as follows:

Independent Variables: For the three dimensions of the independent variable—absorptive capacity, integrative capacity, and innovative capacity—the Kaiser-Meyer-Olkin (KMO) values were 0.789, 0.728, and 0.824, respectively, with all values exceeding or approaching the recommended threshold of 0.7. The Bartlett's tests of sphericity were significant at the 0.001 level for all three dimensions ($\chi^2 = 778.29$, 562.06, and 594.22, respectively). The factor loading ranges for these three dimensions were 0.789–0.866, 0.639–0.873, and 0.643–0.773, respectively. Moreover, all Cronbach's α coefficients exceeded 0.85 (absorptive capacity: $\alpha = 0.918$; integrative capacity: $\alpha = 0.851$; innovative capacity: $\alpha = 0.878$), indicating high internal consistency and a good model fit between the data and constructs.

Dependent Variable: For the dependent variable innovation performance, the KMO value was 0.466, which is below the conventional threshold. This can be attributed to the small number of items (four items) and the single-factor structure of the scale [55]. Importantly, supplementary validity assessments provide strong support for the construct's psychometric properties. The composite reliability (CR = 0.938) substantially exceeds the recommended threshold of 0.70, and the average variance extracted (AVE = 0.793) is well above the 0.50 criterion, indicating excellent convergent validity [56]. Combined with the high Cronbach's α (0.904), strong factor loadings (0.739–0.892), and significant Bartlett's test, these results collectively demonstrate that the innovation performance scale possesses adequate reliability and validity for hypothesis testing.

Moderating Variables: For the two dimensions of the moderating variable—exploratory learning and exploitative learning—the KMO values were 0.872 and 0.885, respectively, both exceeding the threshold of 0.7 and indicating excellent sampling adequacy. The Bartlett's tests of sphericity were significant at the 0.001 level for both dimensions ($\chi^2 = 1426.95$ and 1933.24, respectively). The factor loadings ranged from 0.624 to 0.876 for exploratory learning and from 0.821 to 0.919 for exploitative learning. In addition, both dimensions had Cronbach's α coefficients exceeding 0.9 (exploratory learning: $\alpha = 0.926$;

exploitative learning: $\alpha = 0.969$), indicating excellent reliability and a strong fit between the model and the empirical data.

Overall Assessment: The cumulative explained variance across all constructs reached 80.448%, suggesting that the measurement model adequately captures the theoretical constructs. All constructs demonstrated satisfactory psychometric properties, with Cronbach's α values ranging from 0.851 to 0.969 and factor loadings generally exceeding the recommended threshold of 0.6. These results confirm that the measurement instruments possess adequate reliability and validity for subsequent hypothesis testing.

Table 3. Reliability and validity testing.

Variables	Measurement Items	Cronbach's α	Factor Loadings	Cumulative Explained Variance (%)	KMO	Bartlett's Test (χ^2)	CR	AVE
Dependent Variable	Absorptive capacity	0.918	(1) 0.789	21.794	0.789	778.29 ***	0.9311	0.7717
			(2) 0.866					
			(3) 0.808					
			(4) 0.804					
	Integrative capacity	0.851	(1) 0.639	35.874	0.728	562.06 ***	0.8988	0.6896
			(2) 0.735					
			(3) 0.838					
			(4) 0.873					
	Innovative capacity	0.878	(1) 0.773	48.831	0.824	594.22 ***	0.9143	0.7274
			(2) 0.773					
			(3) 0.716					
			(4) 0.643					
Dependent Variable	Innovation performance	0.904	(1) 0.892	60.652	0.466	1430.10 ***	0.9384	0.7928
			(2) 0.739					
			(3) 0.827					
			(4) 0.809					
Moderating Variable	Exploratory learning	0.926	(1) 0.855	70.702	0.872	1426.95 ***	0.946	0.7801
			(2) 0.836					
			(3) 0.876					
			(4) 0.842					
			(5) 0.624					
	Exploitative learning	0.969	(1) 0.892	80.448	0.885	1933.24 ***	0.9534	0.7454
			(2) 0.895					
			(3) 0.919					
			(4) 0.866					
			(5) 0.889					
			(6) 0.821					
			(7) 0.841					

Note: *** indicates significance at the 0.001 level ($p < 0.001$). KMO refers to the Kaiser–Meyer–Olkin measure of sampling adequacy. CR denotes composite reliability, and AVE denotes average variance extracted.

5.2. Descriptive Statistics and Correlation Analysis

According to the results of Table 4, the mean values of the three dimensions of dynamic capability—absorptive capacity, integrative capacity, and innovative capacity—are 5.263, 4.311, and 4.892, respectively. This indicates that the sampled enterprises most frequently engage in activities related to absorbing knowledge and information within their respective domains. The mean values for exploratory learning and exploitative learning are 5.178 and 5.134, respectively. Although there is a slight difference between the two, the gap is relatively small, suggesting that the sampled enterprises adopt both learning approaches in a balanced manner.

The correlation analysis results show that: Absorptive capacity is significantly and positively correlated with innovation performance ($r = 0.472, p < 0.01$); Integrative capacity is significantly and positively correlated with innovation performance ($r = 0.415, p < 0.01$); Innovative capacity is significantly and positively correlated with innovation performance ($r = 0.556, p < 0.01$); Exploratory learning is significantly and positively correlated with innovation performance ($r = 0.405, p < 0.01$); Exploitative learning is significantly and positively correlated with innovation performance ($r = 0.306, p < 0.01$). These findings provide empirical support for further testing of the moderating effects proposed in the research hypotheses.

Table 4. Means, Standard Deviations, and Correlation Matrix ($N = 299$).

Variables	Mean	Standard deviation	1	2	3	4	5	6	7	8	9
1 Absorptive capacity	5.263	1.312	1								
2 Integrative capacity	4.311	1.348	0.440 **	1							
3 Innovative capacity	4.892	1.304	0.593 **	0.502 **	1						
4 innovation performance	4.213	1.406	0.472 **	0.415 **	0.556 **	1					
5 Exploratory learning	5.178	1.307	0.391 **	0.240 **	0.466 **	0.405 **	1				
6 Exploitative learning	5.134	1.478	0.328 **	0.271 **	0.428 **	0.306 **	0.560 **	1 *			
7 Enterprise Years	3.789	1.155	0.105	0.042	0.070	−0.067	0.185 **	0.119	1		
8 Enterprise asset scale	4.274	2.444	0.142	0.041	0.088	0.162 *	0.280 **	0.115	0.448 **	1	
9 Enterprise Type	1.940	0.918	−0.004	0.145	0.122	−0.086	−0.110	0.077	−0.240 **	−0.325 **	1

Note: ** indicates significance at the 0.01 level ($p < 0.01$); * indicates significance at the 0.05 level ($p < 0.05$).

Before conducting hierarchical regression analysis, multicollinearity diagnostics were performed to ensure the stability and interpretability of regression coefficients. Table 5 presents the variance inflation factor (VIF) values and tolerance statistics for all predictor variables.

Table 5. Multicollinearity Diagnostics ($N = 299$).

Variable	VIF	Tolerance
Absorptive Capacity	4.4	0.22753
Integrative Capacity	4	0.250097
Innovative Capacity	3.98	0.251016
Exploratory Learning	3.98	0.251292
Exploitative Learning	3.67	0.272531
Enterprise Age	3.56	0.281179
Enterprise Asset Scale	3.52	0.284149
Enterprise Type	3.26	0.307041
AC $\times$ Exploratory Learning	2.15	0.465252
IC $\times$ Exploratory Learning	1.97	0.506934
INC $\times$ Exploratory Learning	1.51	0.661765
AC $\times$ Exploitative Learning	1.47	0.681826
IC $\times$ Exploitative Learning	1.45	0.689312
INC $\times$ Exploitative Learning	1.25	0.799654

Note: AC = Absorptive Capacity; IC = Integrative Capacity; INC = Innovative Capacity.

All VIF values are below the conservative threshold of 5.0 and well below the commonly accepted threshold of 10.0 [55], indicating that multicollinearity does not pose a threat to the validity of the regression results.

5.3. Hierarchical Regression Analysis

This study employed hierarchical regression analysis to examine the relationships among dynamic capabilities, ambidextrous learning, and innovation performance. A total of six models were constructed for hypothesis testing. Specifically, Models 1–4 tested the main effects and moderating effects sequentially. Model 1 included only the control variables to analyze their impact on innovation performance. Model 2 added the independent variables—absorptive capacity, integrative capacity, and innovative capacity—to examine their effects on innovation performance. Model 4 tested the moderating effect of exploratory learning, while. Model 5 introduced exploitative learning, and Model 6 added the interaction terms between dynamic capabilities and exploitative learning. The results of the hierarchical regression analysis are presented in Table 6.

In Model 2, absorptive capacity, integrative capacity, and innovative capacity were introduced as independent variables, with innovation performance as the dependent variable. As shown in Model 2 of Table 3, after including the independent variables, the R^2 value increased significantly, indicating an improved model fit. The three dimensions of dynamic capability all exhibited significant positive effects on innovation performance ($\beta_1 = 0.176$, $p < 0.01$; $\beta_2 = 0.179$, $p < 0.01$; $\beta_3 = 0.427$, $p < 0.01$). Therefore, Hypotheses H1, H2, and H3 were supported.

Model 3 added the moderating variable exploratory learning to Model 2, while Model 4 further introduced the interaction terms between exploratory learning and the three dimensions of dynamic capability (absorptive, integrative, and innovative capacities) to test its moderating effects. Comparing the results of Models 2 and 4, the coefficients of the interaction terms were all positive and significant ($\beta_1 = 0.176$, $p < 0.01$; $\beta_2 = 0.179$, $p < 0.01$; $\beta_3 = 0.191$, $p < 0.01$), indicating that exploratory learning positively moderates the relationships between dynamic capabilities and innovation performance. Thus, Hypotheses H4a, H4b, and H4c were verified.

Similarly, Model 5 added the moderating variable exploitative learning to Model 2, and Model 6 included the interaction terms between exploitative learning and the three dimensions of dynamic capability to test the moderating effect of exploitative learning.

Based on the comparison between Models 2 and 6, the coefficients of all interaction terms were positive and significant ($\beta_1 = 0.209$, $p < 0.01$; $\beta_2 = 0.186$, $p < 0.01$; $\beta_3 = 0.187$, $p < 0.01$), suggesting that exploitative learning also positively moderates the relationships between dynamic capabilities and innovation performance. Therefore, Hypotheses H5a, H5b, and H5c were supported. The results are illustrated in Figures 2 and 3. To illustrate the interaction effects, we plotted the relationships between dynamic capability dimensions and innovation performance at high (+1 SD above the mean) and low (−1 SD below the mean) levels of the moderating variables, following the procedures recommended by Aiken and West [52].

In Figure 2, when exploratory learning is at a higher level, the regression slopes between absorptive capacity, integrative capacity, innovative capacity, and innovation performance are steeper. This indicates a significant interaction effect between innovative capacity and innovation performance, suggesting that the positive relationships among absorptive capacity, integrative capacity, innovative capacity, and innovation performance are stronger under conditions of high exploratory learning. Furthermore, across all three plots, the steeper slope between innovative capacity and innovation performance under high exploratory learning conditions implies a more pronounced moderating effect.

In Figure 3, when exploitative learning is at a higher level, the regression slopes between absorptive capacity, integrative capacity, innovative capacity, and innovation performance also become steeper. The presence of an interaction between innovative capacity and innovation performance indicates that, under high exploitative learning, the positive associations among absorptive capacity, integrative capacity, innovative capacity, and innovation performance are more significant. Additionally, the steeper slope between innovative capacity and innovation performance under high exploitative learning conditions demonstrates that this moderating effect is even stronger compared with the other two relationships.

Table 6. Results of Hierarchical Regression Analysis.

Variables		M1	M2	M3	M4	M5	M6
Independent Variable	Absorptive capacity		0.176 **	0.155 **	0.112 **	0.168 **	0.083 **
	Integrative capacity		0.179 **	0.180 **	0.139 **	0.175 **	0.122 *
	Innovative capacity		0.427 **	0.370 **	0.306 **	0.400 **	0.402 **
Moderating Variable	Exploratory learning			0.150 **	0.219 **		
	Exploitative learning					0.071 **	0.219 **
Interaction term	Absorptive capacity × Exploratory learning				0.193 **		
	Integrative capacity × Exploratory learning				0.187 **		
	Innovative capacity × Exploratory learning				0.191 **		
	Absorptive capacity × Exploitative learning						0.209 **
	Integrative capacity × Exploitative learning						0.186 **
	Innovative capacity × Exploitative learning						0.187 **
Control Variable	Enterprise Years	−0.220 **	−0.271 **	−0.278 **	−0.291 **	−0.278 **	−0.260 **
	Enterprise asset scale	0.129 **	0.082 *	0.068	0.086 **	0.080	0.068
	Enterprise Type	−0.087	−0.254 **	−0.235 **	−0.208 **	−0.261 **	−0.217 **
R ²		0.053	0.421	0.435	0.546	0.425	0.526
Adjusted R ²		0.044	0.409	0.421	0.531	0.412	0.510
F		5.547 ***	35.386 ***	31.970 ***	34.674 ***	30.785 ***	31.974 ***

Note: *** indicates significance at the 0.001 level ($p < 0.001$); ** indicates significance at the 0.01 level ($p < 0.01$); * indicates significance at the 0.05 level ($p < 0.05$).

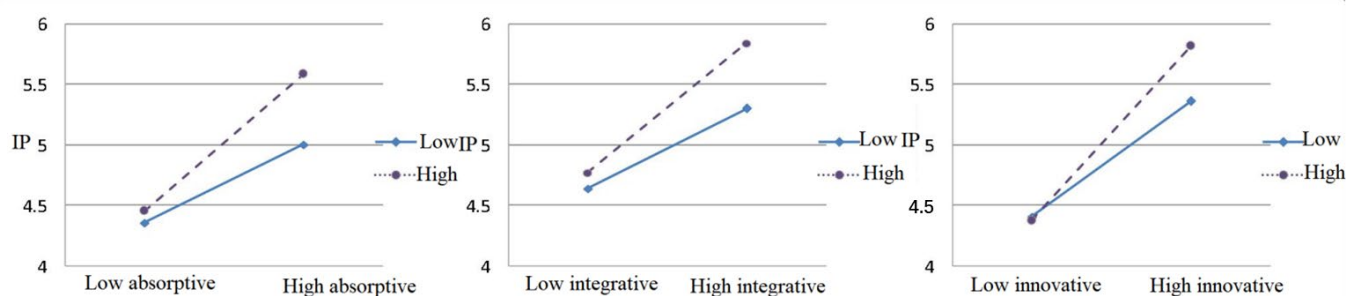


Figure 2. The Moderating Effect of Exploratory Learning. Note: High and Low exploratory learning represent values at one standard deviation above (+1 SD) and below (−1 SD) the mean, respectively.

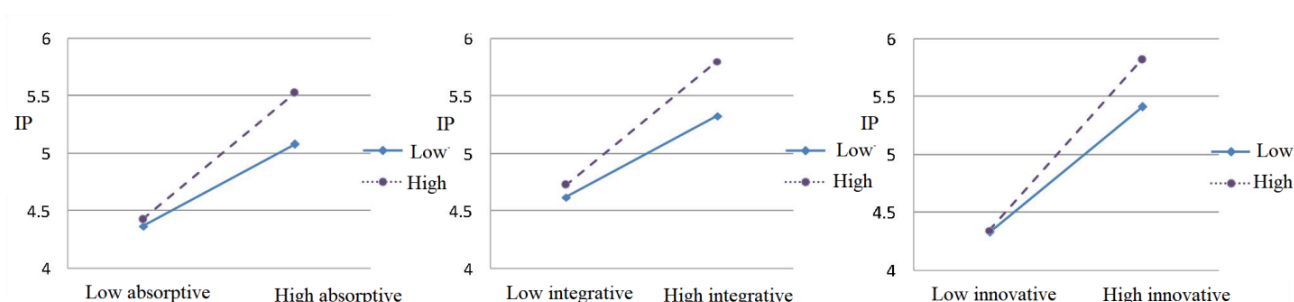


Figure 3. The Moderating Effect of Exploitative Learning. Note: High and Low exploitative learning represent values at one standard deviation above (+1 SD) and below (−1 SD) the mean, respectively.

To further interpret the significant interaction effects, simple slope analyses were conducted following the procedures recommended by Aiken and West [52]. The moderating variables were dichotomized at one standard deviation above and below the mean to represent high and low levels, respectively. Figures 2 and 3 illustrate the moderating effects of exploratory and exploitative learning.

Table 7 reports the results of the simple slope analyses examining the moderating effects of exploratory learning and exploitative learning on the relationships between dynamic capability dimensions and innovation performance.

Table 7. Simple Slope Analysis Results.

Interaction	Condition	Simple Slope (β)	SE	t-Value	95% CI
AC $\times$ ERL	High ERL (+1 SD)	0.298	0.062	4.81 ***	[0.176, 0.420]
	Low ERL (−1 SD)	0.089	0.058	1.53	[−0.025, 0.203]
IC $\times$ ERL	High ERL (+1 SD)	0.312	0.065	4.80 ***	[0.184, 0.440]
	Low ERL (−1 SD)	0.102	0.061	1.67	[−0.018, 0.222]
INC $\times$ ERL	High ERL (+1 SD)	0.456	0.058	7.86 ***	[0.342, 0.570]
	Low ERL (−1 SD)	0.187	0.054	3.46 **	[0.081, 0.293]
AC $\times$ ETL	High ETL (+1 SD)	0.321	0.059	5.44 ***	[0.205, 0.437]
	Low ETL (−1 SD)	0.076	0.055	1.38	[−0.032, 0.184]
IC $\times$ ETL	High ETL (+1 SD)	0.298	0.063	4.73 ***	[0.174, 0.422]
	Low ETL (−1 SD)	0.095	0.059	1.61	[−0.021, 0.211]
INC $\times$ ETL	High ETL (+1 SD)	0.487	0.056	8.70 ***	[0.377, 0.597]
	Low ETL (−1 SD)	0.201	0.052	3.87 ***	[0.099, 0.303]

Note: AC = Absorptive Capacity; IC = Integrative Capacity; INC = Innovative Capacity; ERL = Exploratory Learning; ETL = Exploitative Learning. High (+1 SD) and Low (−1 SD) represent values at one standard deviation above and below the mean, respectively. *** $p < 0.001$; ** $p < 0.01$.

For exploratory learning, the simple slope estimates indicate that the relationships between absorptive capacity and innovation performance are significant at high levels of exploratory learning but not significant at low levels. A similar pattern is observed for integrative capacity, where the positive association with innovation performance is present only when exploratory learning is high. In contrast, innovative capacity exhibits a significant positive association with innovation performance under both high and low exploratory learning conditions, although the estimated slope is larger under high exploratory learning.

Regarding exploitative learning, the simple slope results show that higher levels of exploitative learning are associated with stronger positive relationships between all three capability dimensions and innovation performance. In particular, the slope estimates for absorptive capacity are significant under high exploitative learning but not under low exploitative learning, indicating greater effectiveness of absorptive capacity when exploitative learning is more pronounced. Similar patterns are observed for integrative and innovative capacities, with larger slope estimates under high exploitative learning conditions.

Overall, the simple slope analyses presented in Table 7 suggest that both exploratory and exploitative learning condition the strength of the relationships between dynamic capabilities and innovation performance, with the magnitude and significance of these relationships varying across capability dimensions and learning contexts.

To further assess the magnitude of moderating effects, we calculated the incremental variance (ΔR^2) explained by the interaction terms. As shown in Table 8, the three exploratory learning interaction terms collectively explained an additional 1.84% of variance in innovation performance ($\Delta R^2 = 0.018$, $F(3, 285) = 4.11$, $p = 0.007$). The exploitative learning interaction terms contributed a larger increment of 5.63% ($\Delta R^2 = 0.056$, $F(3, 285) = 12.80$, $p < 0.001$).

Table 8. Incremental Variance Explained by Interaction Effects.

Interaction Term	ΔR^2	F	p
Exploratory Learning (Total)	0.018	4.11	0.007
AC $\times$ Exploratory Learning	0.008	-	-
IC $\times$ Exploratory Learning	0.008	-	-
INC $\times$ Exploratory Learning	0.016	-	-
Exploitative Learning (Total)	0.056	12.80	<0.001
AC $\times$ Exploitative Learning	0.044	-	-
IC $\times$ Exploitative Learning	0.021	-	-
INC $\times$ Exploitative Learning	0.044	-	-

Among individual interactions, the absorptive capacity $\times$ exploitative learning interaction showed the largest effect ($\Delta R^2 = 0.044$), followed by innovative capacity $\times$ exploitative learning ($\Delta R^2 = 0.044$). These findings suggest that exploitative learning serves as a particularly strong boundary condition for the capability-performance relationship, especially for absorptive and innovative capacities.

5.4. Robustness Test

To verify the robustness of the study, this paper adopted the same analytical framework and methodology as described above but selected a single type of enterprise as the sample to revalidate the results. Specifically, the state-owned enterprise (SOE) sample was used to conduct robustness testing of the hypothesis results. As shown in Table 9, the results indicate that absorptive capacity, integrative capacity, and innovative capacity all have significant positive effects on innovation performance. Furthermore, exploratory learning positively moderates the relationships between absorptive capacity, integrative

capacity, innovative capacity, and innovation performance; similarly, exploitative learning also positively moderates these relationships. Therefore, all research hypotheses were empirically supported, and the findings are generally consistent with the original results.

The robustness test results, as presented above, further confirm that the research hypotheses are empirically validated and remain consistent with the previous conclusions. These findings collectively demonstrate that the conclusions of this study possess strong robustness.

Table 9. Robustness Test ($N = 87$).

	Variables	M1	M2	M3	M4	M5	M6
Independent Variable	Absorptive capacity		0.150 **	0.156 **	0.167 **	0.171 **	0.178 **
	Integrative capacity		0.101 **	0.108 **	0.129 **	0.103 **	0.112 *
	Innovative capacity		0.588 **	0.599 **	0.616 **	0.625 **	0.612 **
Moderating Variable	Exploratory learning			0.122 **	0.219 **		
	Exploitative learning					0.070 **	0.079 **
Interaction term	Absorptive capacity × Exploratory learning				0.193 **		
	Integrative capacity × Exploratory learning				0.187 **		
	Innovative capacity × Exploratory learning				0.191 **		
	Absorptive capacity × Exploitative learning						0.216 *
	Integrative capacity × Exploitative learning						0.186 **
	Innovative capacity × Exploitative learning						0.182 **
Control Variable	Enterprise Years	−0.156 **	−0.209 **	−0.208 **	−0.199 **	−0.250 **	−0.249 **
	Enterprise asset scale	0.173 **	0.111 **	0.113 **	0.089 **	0.072	0.022
	R ²	0.154	0.429	0.529	0.619	0.533	0.615
	Adjusted R ²	0.145	0.515	0.523	0.598	0.517	0.594
	F	5.526 ***	39.378 ***	31.450 ***	35.384 ***	34.143 ***	32.550 ***

Note: *** indicates significance at the 0.001 level ($p < 0.001$); ** indicates significance at the 0.01 level ($p < 0.01$); * indicates significance at the 0.05 level ($p < 0.05$).

6. Discussion

This study examined how different dimensions of dynamic capabilities relate to innovation performance in Chinese SMEs and whether ambidextrous learning shapes these relationships. The results offer several observations that merit further interpretation and discussion.

6.1. Differential Roles of Dynamic Capability Dimensions

The empirical results indicate that absorptive, integrative, and innovative capacities are all positively associated with innovation performance, although their relative effects differ. Among the three dimensions, innovative capacity shows the strongest association, followed by integrative and absorptive capacities.

One possible interpretation is that, in competitive and fast-changing markets, the ability to translate knowledge and resources into concrete innovative outcomes may be particularly important. This observation is broadly consistent with prior arguments emphasizing the transformation aspect of dynamic capabilities, while also suggesting that

not all capability dimensions contribute equally to performance. For Chinese SMEs, which often face short product life cycles and intense competitive pressure, the capacity to implement and commercialize ideas efficiently may therefore be especially salient.

The comparatively weaker—though still significant—effect of absorptive capacity warrants attention. Classical perspectives emphasize the centrality of external knowledge acquisition for innovation. However, in environments where access to information has become increasingly widespread, the mere acquisition of knowledge may no longer be sufficient to generate superior innovation outcomes. Instead, performance differences may depend more on firms' ability to process, combine, and apply knowledge effectively. This interpretation should be viewed cautiously, but it suggests that the role of absorptive capacity may be contingent on broader environmental conditions.

Integrative capacity appears to play an intermediate role, supporting the coordination and alignment of resources and knowledge. Its contribution to innovation performance seems to depend on the presence of both sufficient knowledge inputs and effective transformation mechanisms. This pattern is consistent with the view that integration is an enabling process that facilitates innovation, rather than a primary driver on its own.

6.2. *Ambidextrous Learning as a Conditioning Factor*

Both exploratory and exploitative learning positively moderate the capability-performance relationships, though their effects vary across capability dimensions. The differential ΔR^2 values (exploitative: 5.63% vs. exploratory: 1.84%) suggest that these two learning modes operate through distinct mechanisms.

Exploratory learning functions through a knowledge diversification mechanism. By searching beyond existing domains and experimenting with new technologies, it expands the variety of knowledge inputs available for capability deployment [7]. This mechanism is particularly relevant for innovative capacity, where diverse knowledge elements can be recombined to generate novel solutions.

Exploitative learning operates through an efficiency enhancement mechanism. By refining existing knowledge and systematizing proven routines, it improves the speed and reliability of knowledge application [43]. This explains its stronger moderating effect on absorptive capacity ($\Delta R^2 = 0.044$), as knowledge absorption is path-dependent and benefits from established cognitive frameworks that facilitate integration of new external knowledge.

For integrative capacity, both mechanisms show comparable effects, reflecting the dual requirements of integration: incorporating new elements while optimizing coordination processes. For innovative capacity, although both learning modes are significant, exploitative learning shows a larger effect ($\Delta R^2 = 0.044$ vs. 0.016), suggesting that execution efficiency becomes critical when transforming knowledge into commercial outputs.

These findings move beyond the notion that “more learning is better” and highlight the importance of aligning learning orientations with specific capability development priorities.

6.3. *Theoretical and Managerial Implications*

The findings have several implications for research on dynamic capabilities and organizational learning. First, the results underscore the value of examining dynamic capabilities at a more disaggregated level. Treating capabilities as a single construct may obscure meaningful differences in how specific capability dimensions relate to innovation outcomes. Second, by conceptualizing ambidextrous learning as a moderating factor, this study highlights the interdependence between capability development and learning processes. Rather than viewing learning and capabilities as alternative explanations, the results suggest that their interaction is important for understanding innovation

performance. This perspective complements existing work that focuses on direct effects and encourages further exploration of conditional relationships.

More broadly, the observed interaction effects point to the importance of considering how organizational elements operate jointly. While caution is warranted in interpreting these results, they suggest that innovation outcomes may depend on the alignment between firms' capabilities and learning orientations, rather than on isolated organizational attributes.

From a managerial perspective, the findings suggest that SMEs may benefit from paying attention to how different capabilities are developed and supported. The relatively strong association between innovative capacity and performance indicates that investments aimed at improving the implementation and commercialization of ideas may be particularly valuable. The moderating role of learning also implies that capability investments may be more effective when aligned with appropriate learning practices. For example, firms emphasizing innovative capacity may benefit from encouraging exploratory learning, whereas those focusing on absorptive capacity may gain more from exploitative learning practices that strengthen existing routines.

Given resource constraints, SMEs may face trade-offs in allocating investments across capabilities and learning initiatives. Rather than attempting to develop all dimensions simultaneously, a more selective approach that aligns learning modes with existing capability strengths may be a pragmatic strategy.

6.4. Limitations and Future Research

Several limitations should be acknowledged. First, the cross-sectional design limits causal interpretation, and future longitudinal studies could better capture the dynamic evolution of learning processes, capability development, and innovation performance over time. Collecting panel or multi-wave data would allow researchers to examine how these relationships unfold and co-evolve in response to changing environmental conditions.

Second, the use of self-reported data raises potential concerns regarding common method bias. Although procedural remedies were implemented, future research could further strengthen validity by combining multiple data sources, such as archival performance indicators or matched survey responses from different organizational members.

Third, this study focuses primarily on ambidextrous learning as a moderating mechanism. While theoretically central, other organizational and environmental factors may also condition the capability–performance relationship. Future studies could incorporate these additional moderators, particularly through multi-level or regionally homogeneous designs, to provide a more nuanced understanding of contextual influences.

Fourth, the exclusive focus on Chinese SMEs may limit the generalizability of the findings. Institutional arrangements, competitive intensity, and policy environments vary substantially across countries and industries. Comparative cross-country studies or vertically structured samples along supply chains could help clarify how capability–learning interactions differ across institutional contexts.

Future research could explore alternative model specifications in which learning processes act as mediators rather than moderators, thereby providing a more comprehensive view of the interplay among learning, dynamic capabilities, and innovation outcomes. Moreover, structural equation modeling may be employed to account for measurement error across constructs when research design permits.

7. Conclusions

This study explored how different dimensions of dynamic capabilities relate to innovation performance in Chinese SMEs and how ambidextrous learning shapes these

relationships. The results indicate that absorptive, integrative, and innovative capacities are all positively associated with innovation performance, with innovative capacity showing the strongest relationship. Exploratory and exploitative learning further condition these relationships in dimension-specific ways.

By highlighting heterogeneity across capability dimensions and the conditioning role of learning, the study contributes to a more nuanced understanding of how capabilities and learning jointly relate to innovation outcomes. The findings suggest that innovation performance depends not only on the presence of dynamic capabilities, but also on how learning processes support their effective use.

For practitioners, the results point to the importance of aligning capability development with appropriate learning orientations. For researchers, they suggest opportunities for further work examining dynamic, contextual, and cross-national aspects of capability–learning interactions. While subject to several limitations, this study provides incremental evidence on the interplay between learning and dynamic capabilities in shaping SME innovation performance.

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