The effects of ambidextrous learning on exaptation: the moderating role of knowledge scope and knowledge reconstruction ability

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Abstract

Purpose – Exaptation is an important source of enterprise innovation, and its antecedents have attracted extensive attention. Drawing on the knowledge ecosystem theory, organizational learning theory, knowledge-based view and dynamic capability theory, this study focuses on how ambidextrous learning (AL) (exploratory and exploitative learning) affects exaptation and examines how knowledge scope (KS) and knowledge reconstruction ability (KRA) moderate the relationship between AL and exaptation.

Design/methodology/approach – Hypotheses were tested via hierarchical linear regression (SPSS) on 354 firm-level questionnaires from Chinese enterprises.

Findings – The results revealed that exploratory and exploitative learning improve exaptation, whereas KS and KRA, respectively, enhance the relationship between AL and exaptation. Further analysis demonstrated that the interaction between KS and KRA significantly strengthened the relationship between exploratory learning and exaptation, while the interaction failed to enhance the relationship between exploitative learning and exaptation.

Practical implications – The study suggests that high-tech firms should engage in both exploratory learning external and exploitative learning activities to promote exaptation. Moreover, leveraging KS and KRA can enhance exaptation.

Originality/value – This study contributes to the literature on AL outcomes by empirically exploring the effects of exploratory and exploitative learning on exaptation, thus extending the application field of the organizational learning theory. Additionally, by revealing the contingency effects of KS and KRA, this study enriching the research on knowledge-based view and dynamic capabilities theory. Furthermore, the research findings can provide helpful implications for enterprises to achieve exaptation effectively.

Keywords Exploratory learning, Exploitative learning, Exaptation, Knowledge scope, Knowledge reconstruction ability

Paper type Research article

1. Introduction

Exaptation, a novel innovation paradigm, enables cost-efficient industrial transformation and occasionally spawns new markets (Dew *et al.*, 2004; Cattani, 2005). As a strategic mechanism, it has gained prominence in strategic management research for its links to innovative product development (Andriani and Kaminska, 2021), new market creation (Omezzine and Bodas Freitas, 2022), breakthrough innovation (Tang *et al.*, 2022a, b), business model innovation (Codini *et al.*, 2022), niche construction (Dew and Sarasvathy, 2016) and crisis management (Ardito *et al.*, 2021). Meanwhile, China's 2023 Patent Survey reveals that 50% of enterprise

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patents remain dormant (Nie *et al.*, 2024), signaling severe resource misallocation and stifling endogenous innovation. Exaptation addresses this challenge through its reverse-innovation logic: creating markets from existing technologies (Gould and Vrba, 1982; Ren *et al.*, 2019). By repurposing underutilized technologies firms can activate dormant knowledge (Garud *et al.*, 2018) and bridge the gap between R&D accumulation and commercial application (Ma and Li, 2022). Consequently, elucidating how firms implement strategic actions to achieve exaptation has been a central but unexplored research topic.

Drawing upon the knowledge ecosystem (Por and Molloy, 2000; Yang *et al.*, 2022), exaptation is a process of knowledge flow, linking, coupling and innovation inside and outside the organization (Abatecola *et al.*, 2016), including three links of knowledge input, production and output (Beltagui *et al.*, 2020; Li *et al.*, 2022). To activate exaptation, firms must cultivate diverse knowledge repositories while proactively exploring distant opportunities to trigger functional shifts (Cattani, 2005; Abatecola *et al.*, 2016). Ambidextrous learning (AL) (exploratory vs. exploitative learning) serves as the strategic linchpin (March, 1991). According to the theory of organizational learning, exploratory learning drives novelty-seeking through experimentation and risk-taking (Katila and Ahuja, 2002), whereas exploitative learning focuses on efficiency-driven refinement of existing knowledge (Levinthal and March, 1993). While prior research confirms amidextrous learning impact on product innovation (Duan and Gu, 2021), eco-innovation (Huang *et al.*, 2020), and firm innovation (Tho and Duc, 2021; Cheng *et al.*, 2024), its role in enabling exaptation remains theoretically underexplored. Thus, it is necessary to explore its antecedents and to know how to cultivate exaptation, especially from AL perspective.

Furthermore, within knowledge ecosystems, the transformation of knowledge reserves acquired through AL into exaptation is contingent upon contingency factors. The knowledge-based view posits that applying AL outcomes to novel contexts for exaptation fundamentally depends on knowledge characteristics (Argote, 1999; Capaldo *et al.*, 2017; Ren *et al.*, 2019). As a key attribute, knowledge scope (KS)—defined as the breadth of domains a firm masters (D'Este, 2005)—not only facilitates novel idea acquisition and knowledge recombination (Yayavaram and Ahuja, 2008; Shen *et al.*, 2020) but also enables cross-domain linkages for repurposing existing technologies (Garud *et al.*, 2018). Dynamic capabilities theory further explains how firms integrate, reconfigure, and extend resources to create markets (Eisenhardt and Martin, 2000) and sustain innovative advantage in changing environments (Katkalo *et al.*, 2010; Sun *et al.*, 2019; Antonio *et al.*, 2023). Emerging from the intersection of knowledge-based view and dynamic capabilities theory, knowledge reconstruction ability (KRA)—the capacity to repurpose internal/external knowledge in unpredictable contexts (Ye *et al.*, 2016; Li *et al.*, 2022)—enhances both knowledge utilization efficiency (Wang *et al.*, 2020a, b) and cross-network innovation collisions (Zhong *et al.*, 2024). Based on this, some literatures suggests that exaptation requires coupling internal technical resources with external opportunities (Perry-Smith and Mannucci, 2017), where KS-reconstruction synergy benefits inbound and outbound innovation (Chesbrough and Crowther, 2010; Colombelli *et al.*, 2013). Despite these insights, the tripartite interplay between KS, reconstruction ability, and AL remains underexplored, necessitating systematic investigation of their mechanistic roles in ambidextrous-learning-exaptation relationships.

To address these research gaps, this study builds on the knowledge ecosystem framework, organizational learning theory, the knowledge-based view and dynamic capabilities theory, to examine how exploratory and exploitative learning impact exaptation under the condition of different levels of KS and KRA. Accordingly, the contributions of this study are threefold. First, it introduces knowledge ecosystem to interpret the effectiveness of the theoretical model, expanding the application areas of knowledge ecosystems. Second, Based on the organizational learning theory, the linear impacts of AL on exaptation are analyzed, which expands the scope of ambidextrous literature as well as the research of antecedents of exaptation. Third, this study enriches the knowledge-based view and dynamic capabilities theory literature by investigating the moderating role of KS and KRA in AL outcomes. The study further elucidates the important value of knowledge characteristics in generating exaptation. Overall, this study offers novel insights into the mechanisms of AL into exaptation and the boundary conditions of these mechanisms.

2. Theoretical basis and hypotheses development

2.1 Knowledge ecosystems

A knowledge ecosystem is defined as a system of tools and methods that connect knowledge producers and users (Kati *et al.*, 2018), focusing on learning, design, and improvement (Por and Molloy, 2000). It addresses critical issues including knowledge production, identification, value creation, renewal, and integration (Borgh *et al.*, 2012), with demonstrated applications in healthcare (Polese *et al.*, 2018), library sciences (Li *et al.*, 2022), and digital transformation (Marinelli *et al.*, 2024). Research indicates that knowledge ecosystems facilitate optimal utilization of internal and external resources, enabling cross-domain knowledge-sharing, linking, interaction, and application to generate unexpected creative ideas (Huston and Sakkab, 2006; Chesbrough and Chen, 2013). Therefore, the process of achieving exaptation, inherently, falls within the domain of knowledge ecosystems. Drawing on the conceptual framework of knowledge ecosystems and the DICE (Distribution, Interaction, Competition and Evolution) model (Chen *et al.*, 2005), this study posits that realizing exaptation requires constructing a knowledge ecosystem encompassing four core processes: First, knowledge acquisition serves as the foundational stage. Under the open innovation paradigm (Chesbrough, 2004), organizational learning theory emphasizes that firms can integrate internal and external knowledge into their systems—either commercializing internal knowledge through outward channels (via exploitative learning) or acquiring external technologies (via exploratory learning). Thus, the establishment of an AL environment (Filippini *et al.*, 2012) is essential for building knowledge repositories and identifying market opportunities for exaptation. Second, knowledge distribution constitutes a critical precondition, directly influencing exaptation outcomes (Garud *et al.*, 2018). The knowledge-based view suggests that exaptation generation is closely tied to knowledge characteristics, which significantly constrain and shape organizational learning processes and effectiveness (Ren *et al.*, 2019). This study operationalizes knowledge distribution through KS, reflecting interdisciplinary, cross-domain diversity. Third, knowledge integration functions as the dynamic capability that ultimately enhances exaptation performance (Garud *et al.*, 2018). Dynamic capabilities theory offers a way for firms to leverage organizational resources and capabilities to achieve performance benefits (Harrigan *et al.*, 2020). KRA, as a quintessential dynamic capability, facilitates the internalization, assimilation, and recombination of knowledge acquired through AL to drive exaptation. This study operationalizes knowledge integration through KRA, by measuring cross-domain linkage and coupling capabilities. Ultimately, the knowledge innovation emerges as the outcome of exaptation, manifesting through the synergistic effects of knowledge acquisition, distribution, and integration—specifically, the interplay between AL, KS, and KRA. Grounded in knowledge ecosystems, this research establishes a theoretical framework that integrates organizational learning theory, the knowledge-based view, and dynamic capabilities theory to examine how AL, KS, and KRA collectively influence exaptation mechanisms.

2.2 Exaptation

Exaptation is defined as the process of applying existing technologies to new fields or the ability to leverage these technologies to meet emerging demands in novel environments (Mokyr, 2000; Dew *et al.*, 2004; Andriani and Carignani, 2014), and is also interpreted as existing components that initially have little or additional functionality, but are rearranged and combined into a new, more complex form, giving them new functionality (Gregory, 2008). While attracting extensive attention from practitioners and academia, research on the antecedents of exaptation has become a hot issue (Gregory, 2008; Ren *et al.*, 2019). Gould and Vrba (1982) argue that serendipity serves as the triggering mechanism for exaptation. Furthermore, Cattani (2005) pointed out that the realization of exaptation needs two stages: accumulating knowledge and using opportunities. Garud *et al.* (2018) identified three key pathways for inducing exaptation: exaptive pools, exaptive events, and exaptive forums. Some recent research emphasizes the external antecedents of exaptation, such as mergers and acquisitions (Dew *et al.*, 2004; Marquis and Huang, 2010), user innovation (Andriani *et al.*, 2017) and institutional interaction (Garud *et al.*, 2018), whereas others highlight internal antecedents, such as knowledge reserves (Cattani, 2005; Abatecola *et al.*, 2016), patent pools (Wang and Zhao, 2023), organizational structure (Andriani *et al.*, 2017), researchers' analogical abilities (Mastrogiorgio and Gilsing, 2016) and multidisciplinary background (Sedita *et al.*, 2022).

Researchers have tried to untangle the antecedents of exaptation, but some research gaps require further discussion. Specifically, prior research has elucidated both endogenous and exogenous factors underlying exaptation along with its generative mechanisms, including exaptive pools, exaptive events, and exaptive forums (Garud *et al.*, 2018). Scholars have further identified the critical role of accumulated knowledge in forming exaptive pools (Dew *et al.*, 2004; Abatecola *et al.*, 2016). However, the specific mechanisms through which firms accumulate diversified knowledge remain unexplored. Based on the organizational learning theory, as a crucial knowledge accumulation approach, the role of AL in exaptation has been less explored. Furthermore, understanding of how exaptation can be generated is limited by considering the role of organizational learning theory. In this vein, exploring AL-exaptation can add new insights to the antecedents of exaptation.

2.3 Ambidextrous learning and exaptation

Organizational learning emphasizes that organizations adapt to environmental changes through knowledge acquisition, sharing, and application (Huber, 1991), playing a critical role in knowledge creation and technological innovation (Argote, 1999; Lumpkin and Lichtenstein, 2005; Sanz-Valle *et al.*, 2011; Lee *et al.*, 2015). According to organizational learning theory, exploratory learning is defined as the behavior of organizing to search, acquire and master new knowledge (March, 1991). Exploratory learning drives new technology acquisition and opportunity identification (March, 1991; Dew *et al.*, 2004), thereby enhancing strategic foresight to build heterogeneous knowledge reserves (Cattani, 2005). This process fosters an exaptive pool (Garud *et al.*, 2018), sparks unanticipated technology uses (Chesbrough and Chen, 2013) and creative breakthroughs (Garud *et al.*, 2016), and may support institutional reforms enabling exaptation. In contrast, exploitative learning is defined as the behavior of optimizing organizational processes, mining existing resources and refining existing experience (March, 1991). Exploitative learning enables exaptation through functional repurposing of existing technologies (Gould and Vrba, 1982; Perry-Smith and Mannucci, 2017; Wang *et al.*, 2024a,b), facilitating commercialization in new markets. Thus, we argue that exploratory and exploitative learning positively impact exaptation for the following reasons.

As a key mode of organizational learning, exploratory learning facilitates exaptation by seeking novel methods, technologies, and markets in unfamiliar or unexplored domains (March, 1991; Lin *et al.*, 2015), thereby providing diversified knowledge reserves, market opportunities and change support.

First, enterprises' exploratory learning by means of "industry-university-research cooperation" and "user involvement in innovation" (Chesbrough, 2004; Tang *et al.*, 2022a, b) supplies the knowledge base and potential serendipitous discoveries necessary for exaptation by acquiring new technologies (Cattani, 2005; Andriani *et al.*, 2017). Exploratory learning—through the search, acquisition, and utilization of external heterogeneous technological knowledge—expands inventors' cognitive resources and break through the mindset of “not invented here”, furnishing heterogeneous knowledge pool for exaptation (Chesbrough and Chen, 2013; Li *et al.*, 2024) while also establishing a diversified knowledge foundation for novel combinations of old and new knowledge to generate extra-use exaptation (Weible, 2013; Liu *et al.*, 2025). Moreover, the accumulation of diverse knowledge through exploratory learning enhances firms’ sensitivity to market dynamics and industry trends (Feng and Chen, 2022), enabling entrepreneurs to remain alert to contingent events and cultivate unexpected discoveries (Andriani and Carignani, 2014).

Second, exploratory learning triggers exaptation opportunities and fosters innovations that significantly impact the industry (Dew *et al.*, 2004). Lumpkin and Lichtenstein (2005) argue that firms prioritizing exploratory learning are more likely to identify opportunities, while opportunity search and discovery constitute vital phases of exaptation (Cattani, 2005). The existing research shows that exaptation relies more heavily on contexts that diverge from the original functions of existing technologies (Andriani *et al.*, 2017), as more distant knowledge tends to enhance the value of innovation (Capaldo *et al.*, 2017). This suggests that externally acquired heterogeneous knowledge and remote market opportunities obtained through exploratory learning facilitate the emergence of exaptation (Ren *et al.*, 2019). As noted by Cattani and Malerba (2021), exploratory learning enables firms to identify future market trends and seek distant opportunities, thereby assessing potential unexpected functionalities of existing products and technologies in new environments or advancing novel applications of established technologies (Cattani, 2005). Similarly, Haunschild and Sullivan (2002) found that firms engaged in exploratory learning exhibit strategic foresight and anticipatory capabilities, allowing them to access undeveloped yet high-potential markets and domains, thereby securing competitive advantages in new industries based on their existing knowledge base.

Third, exploratory learning challenges enterprises’ assumptions about mission, customers, and opportunities, breaks path dependence, and liberates them from institutionalization. Moreover, it facilitates revolutionary cross-border innovation—stimulating internal-external knowledge interaction (Ganzaroli *et al.*, 2014), promoting knowledge reorganization and innovation, and enhancing idea originality (Burgelman and Grove, 2007) and innovative problem-solving (Katila and Ahuja, 2002)—thereby improving the transfer of existing technologies to new fields. Therefore, the following hypothesis was proposed:

H1. Exploratory learning positively affects exaptation.

As an alternative mode of organizational learning (March, 1991), exploitative learning builds upon existing technological trajectories to enhance internal resource efficiency through refinement, extension, and improvement of established knowledge, thereby maximizing its innovative potential (Levinthal and March, 1993; McCarthy *et al.*, 2017). This study posits that exploitative learning offers an alternative mechanism for enabling exaptation.

First, exploitative learning establishes the technical foundation for exaptation through knowledge outflows (Garud *et al.*, 2016). By continuously mining the potential of existing knowledge and technologies through the path of “technology development”, it facilitates knowledge integration, flow, and dissemination (Ding *et al.*, 2020). On one hand, exploitative learning deepens R&D personnel’s the breadth and depth of understanding of product functionalities, break through the constraints of old conventions, enhance creativity, enabling module redesign to create more complex technical forms with novel applications (Gregory, 2008), thus creating technical conditions for functional transfer (Kim and Tuahene-Gima, 2010). On the other hand, through decomposition and refinement of existing components, it expands a technology’s exaptive possibilities (Dew *et al.*, 2004; Andriani and Carignani, 2014).

Second, exploitative learning facilitates novel contextual applications of existing technologies (Berchicci, 2013; Andriani *et al.*, 2024). Exploitative learning focuses on continuous in-depth understanding, absorption and expansion of existing products in the form of “technology sharing”, and technologies through refining, integration, extension and transformation, which not only stimulates new perspectives and ways to solve problems, but also helps to promote cross-border thinking and creativity (Caner and Tyler, 2015); But also insight into the new market space with low cost and high efficiency in the way of "ecological co-construction", and explore the application value of existing technologies in new fields or new scenes through extension (Ghemawat *et al.*, 1993; Jin *et al.*, 2025), thus forming exaptation (Arthur, 2007; Lin *et al.*, 2015). Therefore, the following hypothesis is proposed:

H2. Exploitative learning positively affects exaptation.

2.4 The moderating effect of knowledge scope

The knowledge-based view emphasizes that knowledge diversity is an important condition for technological innovation (Soto-Acosta *et al.*, 2018; Zhang *et al.*, 2024). The KS refers to the range of domains encompassed by an enterprise's knowledge, playing a crucial role in integrating knowledge across various fields, particularly within complex technological domains (Luo, 2009). This KS facilitates the process of exaptation in enterprises through two primary types of learning activities. On the one hand, a broader KS increases opportunities for association, combination, linkage, and innovation (Katila and Ahuja, 2002; Shoaib and Kehinde, 2019). Specifically, a wide-ranging knowledge base enhances the ability to identify and understand the connections between new and existing knowledge, thus fostering conditions for the cross-disciplinary integration of internal and external insights. Furthermore, a more expansive KS is more likely to yield "happy surprises", which refers to the unexpected application of concepts from one field to another (Luo, 2009). Conversely, knowledge derived from disparate fields or that deviates from the core business can serve as a significant catalyst for stimulating exaptation (Perry-Smith and Mannucci, 2017). This interplay triggers conditions for exploratory learning-driven exaptation. A notable example is Dr Spencer, an employee at Raytheon Company, who serendipitously discovered that a magnetron could melt chocolate. By integrating knowledge from multiple disciplines—including trigonometry, calculus, chemistry, physics, and metallurgy—he conceptualized the microwave oven and submitted a patent application for the "Method of Cooking Food." Recognizing the transformative potential of this innovation, Raytheon launched the world's first microwave oven in 1947, revolutionizing cooking methods (Osepchuk, 1984).

On the other hand, a broader scope of knowledge facilitates the effective utilization of existing knowledge reserves. Diverse knowledge spanning various industries, fields, and networks can spark the reconfiguration of products and technologies. This process connects established technological systems with emerging fields and industries, creating opportunities for novel applications of existing products (Chesbrough and Chen, 2013). Such interactions strengthen the relationship between exploitative learning and exaptation. For instance, at Procter and Gamble, a comprehensive knowledge base has expedited the integration of internal discoveries with external ideas, intensifying the development of exaptation (Huston and Sakkab, 2006).

In contrast, a narrow scope of knowledge can constrain an organization's strategy and business practices within traditional or stable domains, leading to a rigidity of core capabilities. This limitation often results in the organization overlooking valuable new knowledge (Beinhocker, 1999). Companies frequently tackle innovation challenges through localized searches, which diminishes their ability to identify opportunities in novel fields via exploratory learning (Feng and Chen, 2022), thereby hindering the likelihood of exaptation. Furthermore, under conditions of limited KS, strategic foresight is often inadequate, and there is a lack of heightened awareness regarding unexpected events. This deficiency makes it challenging to anticipate potentially transformative new environments based on accumulated knowledge (Garud *et al.*, 2016), which is detrimental to the formation of exaptation. Additionally, the narrowness of knowledge domains restricts the feasibility of exploitative learning, impeding the interaction and integration of knowledge across different areas to foster exaptation. Therefore, the following hypotheses were proposed:

H3. Knowledge scope strengthens the relationship between exploratory learning and exaptation.

H4. Knowledge scope strengthens the relationship between exploitative learning and exaptation.

2.5 The moderating effect of knowledge reconstruction ability

KRA refers to an enterprise's capacity to integrate, configure, and innovate internal/external knowledge in response to environmental changes (Wang *et al.*, 2020a, b). Strong capability enables firms to adapt to market trends, overcome inertia, and embed new knowledge into existing systems, forming interconnected knowledge elements (Ye *et al.*, 2016) that drive learning activities toward exaptation. From the perspective of dynamic capabilities theory, knowledge reconstruction bridges internal and external knowledge. Enhanced capability allows firms to filter valuable resources efficiently, amplifying learning's impact on exaptation. Specifically, agile organizations can rapidly identify and leverage critical knowledge, while integrating heterogeneous technologies from exploratory learning into current systems (Bruno *et al.*, 2018). This fosters knowledge recombination and functional transfer, enabling firms to transcend spatial and cognitive boundaries (Andriani and Carignani, 2014), thereby discovering distant opportunities. For example, Huaxi Biotechnology restructured intelligent design, chemistry, and pressure-cooker knowledge using water machine principles, launching a high-concentration hydrogen-rich water machine. This innovation addressed modern families' health and convenience needs while achieving technological breakthroughs.

KRA enhances exaptation through internal knowledge mining and creative integration. First, it strengthens R&D teams' analogical reasoning and technological comprehension (Mastrogiorgio and Gilsing, 2016), enabling them to decompose and integrate technologies while uncovering hidden functional interdependencies (Andriani and Carignani, 2014). Second, it improves internal knowledge search efficiency and predicts the viability of knowledge combinations, facilitating the fusion of new and existing knowledge (Yu and Yu, 2024). For example, BYD (Build Your Dreams) merged battery R&D expertise with material science to optimize power battery structures, ultimately developing the high-performance "blade battery" with extended durability.

Conversely, weak knowledge reconstruction limits opportunity identification and cross-domain knowledge integration, stifling exaptation. Exaptation thrives at intersections of diverse knowledge (Garud *et al.*, 2016), but low capability restricts bridging internal knowledge with external fields. High path dependence and diminished creativity further impede the processing, decomposition, and transformation of existing technologies, weakening the link between exploitative learning and exaptation. Nokia exemplifies this: its overreliance on Symbian systems and failure to integrate emerging technologies prevented radical innovation amid market shifts, leading to its decline. Therefore, the following hypotheses were proposed:

H5. Knowledge reconstruction ability strengthens the relationship between exploratory learning and exaptation.

H6. Knowledge reconstruction ability strengthens the relationship between exploitative learning and exaptation.

2.6 The joint moderating role of knowledge scope and knowledge reconstruction ability

Beyond their individual roles, KS (diverse knowledge stocks and differentiated structures) and KRA synergistically shape how AL drives exaptation (Colombelli *et al.*, 2013). A broad KS captures external knowledge spillovers while highlighting combinatorial potential (Feng and

Chen, 2022), enabling firms to systematically identify, allocate, and integrate cross-domain resources. This process simultaneously strengthens KRA, which reciprocally enhances firms' capacity to bridge old/new knowledge and generate innovations (Wang *et al.*, 2020a, b). Their interplay forms a self-reinforcing cycle: diverse knowledge stocks fuel reconstruction capabilities, while reconstruction efforts expand KS through novel combinations (Savino *et al.*, 2017).

A wide knowledge spectrum provides structural flexibility for multi-path integration (Wang *et al.*, 2017). When coupled with strong reconstruction ability, organizations can decode complex relationships between existing technologies and emerging insights (Wang and Zhao, 2023), enabling them to assimilate externally acquired knowledge into transformative linkages (Xu *et al.*, 2018). This synergy allows firms to deploy exploratory learning beyond conventional boundaries, forging cross-domain connections (Zeng *et al.*, 2015) that fuel creativity and serendipitous discoveries (Mastrogiorgio and Gilsing, 2016). For instance, unexpected linkages between disparate knowledge domains may reveal latent functions in mature technologies (Cattani, 2005), such as repurposing aerospace materials for medical devices. Conversely, limited KS or weak reconstruction capacity disrupts this dynamic. Narrow knowledge stocks restrict combinatorial possibilities, while poor reconstruction skills hinder the translation of insights into actionable connections. Without this synergy, AL becomes fragmented, reducing exaptation potential. Therefore, the following hypotheses were proposed:

H7. The interaction between knowledge scope and knowledge reconstruction ability strengthens the relationship between exploratory learning and exaptation.

The synergy between KS and KRA drives iterative reuse and innovation of existing technologies (Savino *et al.*, 2017; Zeng *et al.*, 2015). By mining internal knowledge, firms create synergies with cross-domain expertise, enhancing their capacity to repurpose established technologies into novel applications (Carnabuci and Operti, 2013). Specifically, this interaction enables enterprises to reconfigure product components through exploitative learning, unlocking hidden functionalities (Gregory, 2008). For example, deep integration of knowledge modules allows optimization of product performance—such as upgrading a battery's thermal management system to serve both automotive and energy storage sectors—achieving modular exaptation (Andriani and Carignani, 2014).Therefore, the following hypotheses were proposed:

H8. The interaction between knowledge scope and knowledge reconstruction ability strengthens the relationship between exploitative learning and exaptation.

The research model is shown in Figure 1.

3. Methodology

3.1 Samples and data collection

This study investigates the impact of AL on exaptation through questionnaire surveys, employing a rigorous three-phase development process. To ensure content validity, we first engaged two associate professors specializing in innovation management and two senior executives with R&D experience to refine ambiguous items. Following this validation, we conducted a pilot test in the Taiyuan Economic and Technological Development Zone, Shanxi Province. We randomly selected five enterprises from the zone's official directory and obtained managerial consent to interview three employees per organization. During these structured interviews, we administered preliminary questionnaires while gathering feedback on comprehension challenges and response accuracy. Subsequent analysis of pilot data and participant insights informed comprehensive revisions to the questionnaire's structure, item wording, and logical flow, ultimately producing a finalized instrument that balances academic

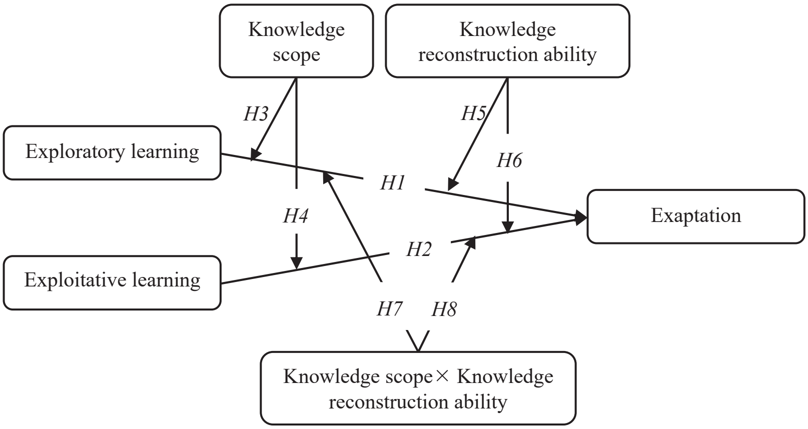

Figure 1. Research model

rigor with practical accessibility, enabling respondents to provide reliable answers based on their practical understanding of exaptation.

Subsequently, this study employed a large-scale questionnaire survey targeting high-tech enterprises in Shanxi, Jiangsu, Shanghai, and Hebei provinces, focusing on managers, technical personnel, and industry-academia-research collaborators as key respondents. The upper echelons theory (Hambrick and Mason, 1984) posits that managers' cognitive backgrounds influence corporate innovation decisions. As key actors in exaptation, managers hold a comprehensive understanding of technological innovation strategies, learning approaches, and knowledge management mechanisms. From the perspective of the community of practice (Choi *et al.*, 2020), the experiential knowledge of technical personnel plays a critical role in innovation iteration. These individuals are directly involved in technological development and possess extensive practical expertise essential for achieving exaptation. Furthermore, the triple helix model underscores the significant impact of industry-university-government collaboration on innovation (Jiménez *et al.*, 2021). Such collaborators provide resource integration strategies that facilitate knowledge flow and collaborative innovation, thereby enabling exaptation. As China has implemented its innovation-driven development strategy since 2012, traditional industries have undergone significant technological transformation, enabling manufacturing sectors to shift from low-end to mid-high-end production while achieving coordinated progress in digitalization, green technologies, and advanced manufacturing. This transition has led increasing numbers of traditional manufacturers to evolve into high-tech enterprises. However, the critical question of how these enterprises maintain sustainable innovation advantages in uncertain environments has drawn substantial attention from both academia and industry (Wanaswa *et al.*, 2021). This study focuses on high-tech enterprises for two principal reasons. First, compared to traditional manufacturers, high-tech enterprises demonstrate more favorable conditions for open innovation, characterized by stronger AL practices, more fluid knowledge flows, and more standardized management mechanisms (Lv *et al.*, 2023). Second, during this crucial economic transformation period, while these enterprises hold numerous invention patents, their technology transfer efficiency remains suboptimal (Nie *et al.*, 2024), creating substantial pressure to adapt existing technologies for sustainable innovation advantages.

To ensure survey validity, we implemented three key measures: (1) verifying respondents' comprehension of concepts related to product innovation, corporate strategy, and industry development; (2) guaranteeing respondent anonymity to minimize participation concerns; and (3) excluding samples containing logical inconsistencies, incomplete responses, or uniform answers.

This study implemented a dual-channel data collection strategy from January to May 2023, combining on-site surveys and online surveys of Master of Business Administration (MBA)/ Executive Master of Business Administration (EMBA) participants. Due to resource constraints, we employed convenience sampling, a non-probability method widely adopted in management and innovation studies (e.g. Zhu *et al.*, 2024). (1) On-site surveys: We leveraged the research team's professional networks, alumni associations, and industry-university-research partnerships. From a compiled enterprise directory, we selected target companies based on accessibility and arranged for research team members or designated managers to distribute questionnaires on-site. This approach resulted in 208 valid responses from 240 distributed questionnaires. (2) Online surveys: The questionnaire was administered to MBA/EMBA students affiliated with the research team's academic networks (including advisors, colleagues, and collaborators) from universities in Shanxi, Hebei, Jiangsu, and Shanghai. These respondents, primarily composed of corporate managers and technical professionals engaged in product innovation or industry-academia collaboration across diverse industries, provided diverse and relevant data for this study. A sample of 190 MBA/ EMBA students was selected and received the questionnaire via email, accompanied by detailed completion guidelines. Follow-up reminders were sent to ensure timely responses, yielding 169 valid questionnaires.

From the total 430 distributed questionnaires (240 on-site + 190 electronic), we collected 377 responses. After eliminating 23 incomplete, inconsistent, illegible, or incorrectly completed questionnaires, we retained 354 valid responses (81.78% effective rate). Sample characteristics are presented in Table 1.

To ensure sample quality and mitigate potential non-response bias and heterogeneity effects from multi-source sampling, we conducted validity tests. First, using Armstrong and Overton's (1977) extrapolation method, we compared early and late respondents on key dimensions (firm size, age, ownership type) and all study variables. The analysis revealed no significant differences ($p > 0.05$), suggesting minimal non-response bias (cf. Chi *et al.*, 2022).

Table 1. Sample characteristics ($N = 354$)

Variable	Items	Frequency	Percentage (%)
Firm age (years)	5–15 years	78	22.03
	16–30 years	223	63.00
	More than 30 years	53	14.97
Firm scale (employee)	Less than 300	24	6.78
	301 and 1,000	53	14.97
	1,001 and 2,000	88	24.86
	2,001 and 3,000	133	37.57
	More than 3,000	56	15.82
Ownership	state-owned	129	36.44
	private-owned	95	26.84
	three-funded	26	7.34
	collective	45	12.71
	Others	59	16.67
Industry	textile and apparel	28	7.91
	furniture	67	18.93
	food processing	94	26.55
	pharmaceutical manufacturing	118	33.33
	Others	47	13.28
Region	Shanxi	117	33.05
	Jiangsu	82	23.16
	Shanghai	56	15.82
	Hebei	99	27.97

Second, we assessed potential differences between on-site and online samples. *F*-tests showed no significant differences (all $p > 0.05$) in study variables (exploratory learning, exploitative learning, exaptation, KS, and KRA) or control variables (firm age, size, ownership type, and industry distribution). Additional independent samples *t*-tests between the two groups further confirmed these results (all $p > 0.05$), justifying the pooling of both samples without threatening the study's validity.

3.2 Variable measurement

The scales employed in this paper are all derived from well-established scales utilized in existing research. To enhance their applicability, the reference scales underwent meticulous translation and back-translation during the design phase, with question items tailored to the unique characteristics of our study. All constructs were measured using 5-point Likert scales, ranging from 1 (strongly disagree) to 5 (strongly agree), to assess the multi-item constructs under investigation. Table 2 lists the measurement items.

AL: Rooted in March's (1991) seminal work, comprises two dimensions: *exploratory learning* (EL_1) and *exploitative learning* (EL_2). Exploratory learning was measured with four items, while exploitative learning included five items. All items were adapted from established scales by Atuahene-Gima and Murray (2007), Chung *et al*. (2015) and Cao (2017).

Table 2. Factor analysis and the results of reliability and validity

Variable	Measurement item	Factor load
EL_1 (α = 0.711, CR = 0.822, AVE = 0.536)	We collect novel information and ideas that went beyond our current market and technological experience	0.767
	We effectively disseminates and shares the obtained new knowledge and technologies internally	0.739
	We collect novel information and ideas that went beyond our current market and technological experience	0.722
	We can quickly use new knowledge and novel technology to develop new market	0.700
EL_2 (α = 0.756, CR = 0.837, AVE = 0.508)	We can effectively identify new knowledge in the field of current technology	0.763
	We can effectively create or externally acquire the required knowledge in the field of current technology	0.747
	We can effectively share the knowledge created or acquired in the field of current technology	0.742
	We can effectively integrate and apply the knowledge created or acquired in the field of current technology	0.699
	Our aim is to search for knowledge and information that we can implement well to ensure productivity	0.602
EXAP (α = 0.837, CR = 0.902, AVE = 0.754)	A technology of our firm has been successfully applied in another field	0.885
	A product of our firm has gained new functions in the new environment	0.881
	We have new functions through the combination of existing product functions	0.838
KS (α = 0.717, CR = 0.845, AVE = 0.645)	Our firm has the knowledge to enhance product functionality and improve product design	0.824
	Our firm has product knowledge of various industries and market segments	0.824
	Our firm combines new ideas from diverse technology or product knowledge	0.759
KRA (α = 0.710, CR = 0.821, AVE = 0.535)	Our firm can understand market opportunities from multiple perspectives	0.750
	New products of our firm integrate diversified technologies and functions	0.747
	Ideas and knowledge of enterprise technological innovation originate from various fields	0.712
	Our firm has a new understanding of market opportunities	0.715

Exaptation (EXAP): Andriani *et al.* (2017) proposed an alternative method for measuring exaptation by analyzing user-driven deviations from original functions using secondary data (e.g. DrugDex, ICD-9-CM). Their quantitative approach provides an effective tool for empirical exaptation research within specific industries. However, measuring exaptation across multiple industries remains an area requiring further exploration (Ren *et al.*, 2019). Recent studies by Tang *et al.* (2022a, b) and Wang and Zhao (2023) introduced a scale-based method, offering another viable measurement tool for exaptation research. Building on the conceptual foundation of exaptation (Adner and Levinthal, 2002; Arthur, 2007; Gregory, 2008) and following Churchill's (1979) scale development paradigm, this study draws on the works of Tang *et al.* (2022a, b) and Wang and Zhao (2023) to develop and refine a three-item exaptation scale. Validation results demonstrate strong psychometric properties, with all standardized factor loadings exceeding 0.80 ($p < 0.001$), composite reliability of 0.902, and average variance extracted of 0.754, confirming the scale's validity.

KS: Based on the research of Feng and Chen (2022), three items were used to measure KS.

KRA: Based on the research of Ye *et al.* (2016), Wang *et al.* (2020a, b), four items were used to measure KRA.

Control variables: Aligned with established methodologies (Yi *et al.*, 2018; Feng and Chen, 2022; Zhu *et al.*, 2024), we controlled for firm age (operationalized as establishment years: 5–15, 16–30, >30), size (employee tiers: <300, 301–1,000, 1,001–2,000, 2,001–3,000, >3,000), ownership (state-owned, private, three-funded, collective and others), and industry (textile/apparel, furniture, food processing, pharmaceuticals manufacturing and others).

3.3 Validity and common method variance tests

In terms of validity, discriminant validity was confirmed as the square roots of AVEs (bolded diagonal elements in Table 4) exceeded all corresponding inter-construct correlations. Convergent validity was established with all AVEs surpassing the 0.50 benchmark (range: 0.508–0.754) and factor loadings exceeding 0.6 (Table 2). Confirmatory factor analysis supported the hypothesized five-factor structure, showing superior fit (χ^2/df = 2.267; comparative fit index = 0.932; Tucker–Lewis index (TLI) = 0.911; goodness of fit index = 0.923; root mean square error of approximation = 0.060) compared to alternative models (Table 3), further verifying discriminant validity.

To assess common method variance, we employed two approaches. First, Harman's single-factor test revealed five components (eigenvalues >1), with the first explaining only 33.098% of variance—below the 50% threshold. Second, following Podsakoff *et al.* (2003), we compared models with/without a common latent variable. All fit index changes (ΔCFI/TLI <0.03; ΔRMSEA/standardized root mean square residual <0.01) were below recommended thresholds, indicating common method variance is not a significant issue (Table 3).

Table 3. Validity test

Model	χ^2/df	CFI	TLI	GFI	RMSEA	SRMR
One factor	6.861	0.633	0.587	0.751	0.129	0.103
Two factors	4.629	0.774	0.744	0.817	0.101	0.049
Three factors	4.328	0.795	0.766	0.834	0.097	0.047
Four factors	2.944	0.889	0.863	0.896	0.074	0.040
Five factors	2.267	0.932	0.911	0.923	0.060	0.035
Five factors + common method factor	1.988	0.954	0.930	0.942	0.053	0.028

Note(s): Five factors: EL_1, EL_2, EXAP, KS, and KRA; four factors: EL_1+ EL_2, EXAP, KS, and KRA; three factors: EL_1+ EL_2, EXAP, KS + KRA; two factors: EL_1+ EL_2+KS + KRA and EXAP; one factor: EL_1+ EL_2+KS + KRA + EXAP

Table 4. Mean, standard deviation, and correlation coefficient

Variable	1	2	3	4	5
EL_1	*0.732*				
EL_2	0.529**	*0.713*			
EXAP	0.276**	0.360**	*0.868*		
KS	0.532**	0.455**	0.347**	*0.803*	
KRA	0.539**	0.432**	0.264**	0.464**	*0.731*
Mean	4.1758	4.1520	3.6064	4.3136	4.0749
Standard deviation	0.5525	0.5550	1.0571	0.5559	0.5751

Note(s): **Significant at the 0.01 level; *significant at the 0.05 level (two-tailed test); the italic data in the diagonal line is the square root value of each variable AVE

4. Results

4.1 Description and correlation

Descriptive statistics were analyzed using SPSS 20.0, with the results presented in Table 4. Significant correlations were observed among the independent variables (exploratory learning and exploitative learning), moderating variables (KS and KRA), and the dependent variable (exaptation). These findings support the suitability of the data for further regression analysis.

4.2 Main effects

Table 5 presents the regression analysis of the independent and dependent variables. Model 1 examines the impact of control variables on exaptation, while Models 2 and 3 assess the effects of exploratory learning and exploitative learning, respectively. Model 2 tests H1, revealing a significant positive relationship between exploratory learning and exaptation ($\beta = 0.275$, $p < 0.001$), thus supporting H1. Similarly, Model 3 tests H2 and demonstrates that exploitative learning also has a significant positive effect on exaptation ($\beta = 0.361$, $p < 0.001$), confirming H2. These results suggest that both exploratory and exploitative learning contribute to exaptation.

4.3 Moderating effects

Table 6 presents the moderating role of KS in the relationship between AL and exaptation. Models 1–2 test H3, showing that KS positively moderates the exploratory learning-exaptation relationship ($\beta = 0.183$, $p < 0.01$), thereby supporting H3. Similarly, Models 3–4 test H4, demonstrating that KS also positively moderates the exploitative learning-exaptation relationship ($\beta = 0.146$, $p < 0.01$), confirming H4. These results indicate that KS enhances both types of learning's effects on exaptation.

Table 5. Analysis results of the effect of ambidextrous learning on exaptation

Variable	Exaptation M1	M2	M3
Firm age	−0.037	−0.046	−0.051
Firm scale	−0.025	−0.008	−0.021
Ownership	−0.067	−0.058	−0.059
Industry	0.020	−0.001	0.021
EL_1		0.275***	
EL_2			0.361***
$\triangle R^2$	0.007	0.082	0.137
F	0.610	6.191***	11.039***

Note(s): ***Significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level

Table 6. Analysis results of the moderating role of the knowledge scope

Variable	Exaptation M1	M2	M3	M4
Firm age	−0.054	−0.064	−0.058	−0.050
Firm scale	0.015	0.010	0.004	−0.006
Ownership	−0.073	−0.068	−0.070	−0.069
Industry	−0.002	0.002	0.010	0.018
EL_1	0.113*	0.168**		
EL_2			0.253***	0.281***
KS	0.113***	0.333***	0.237***	0.254***
EL_1 × KS		0.183**		
EL_2 × KS				0.146**
$\triangle R^2$	1.41	0.168	0.181	0.200
F	9.473***	9.969***	12.751***	11.285***

Note(s): ***Significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level

As shown in Table 7, we examine the moderating role of KRA in the AL-exaptation relationship. For H5, Models 1–2 demonstrate that KRA positively moderates the effect of exploratory learning on exaptation ($\beta = 0.159$, $p < 0.01$), supporting H5. Similarly, Models 3–4 testing H6 reveal a significant positive moderating effect of KRA on the exploitative learning-exaptation relationship ($\beta = 0.123$, $p < 0.05$), thereby confirming H6. These findings collectively indicate that knowledge reconstruction capability enhances both exploratory and exploitative learning's contributions to exaptation.

The moderating effects relationship of the KS, KRA in AL, and exaptation were plotted according to Toothaker (2017) (see Figures 2–6). As displayed in Figure 2, when the KS was at a low level, exploratory learning was positively correlated with exaptation but not significantly ($t = 0.245$, $p > 0.1$). When the KS was at a high level, exploratory learning was positively correlated with exaptation ($t = 3.863$, $p < 0.001$), which proved that the positive effect of exploratory learning on exaptation became stronger with the increase in the KS, and the low level of exploratory learning had no positive effect. As displayed in Figure 3, when the KS was at a low level, the slope of the straight line was smaller ($t = 2.193$, $p < 0.05$), and when the exploitative learning was at a high level, the slope of the straight line was larger ($t = 5.334$ $p < 0.001$). This phenomenon revealed that the positive effect of exploitative learning on

Table 7. Moderating role analysis results of knowledge reconstruction ability

Variable	Exaptation M1	M2	M3	M4
Firm age	−0.050	−0.057	−0.054	−0.054
Firm scale	−0.002	−0.009	−0.012	−0.018
Ownership	−0.066	−0.072	−0.065	−0.068
Industry	0.001	0.003	0.016	0.017
EL_1	0.184**	0.198**		
EL_2			0.302***	0.309***
KRA	0.169**	0.222***	0.136*	0.171**
EL_1 × KRA		0.159**		
EL_2 × KRA				0.123*
$\triangle R^2$	0.102	0.123	0.152	0.166
F	6.552***	6.928***	10.359***	9.806***

Note(s): ***Significant at the 0.001 level; **significant at the 0.01 level; *significant at the 0.05 level

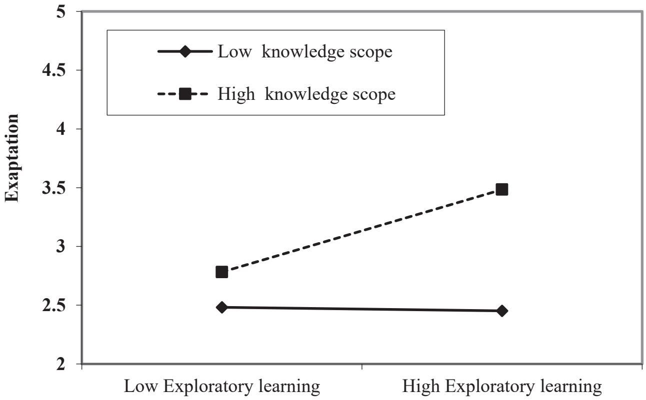

Figure 2. Moderating effect of knowledge scope on the relationship between exploratory learning and exaptation

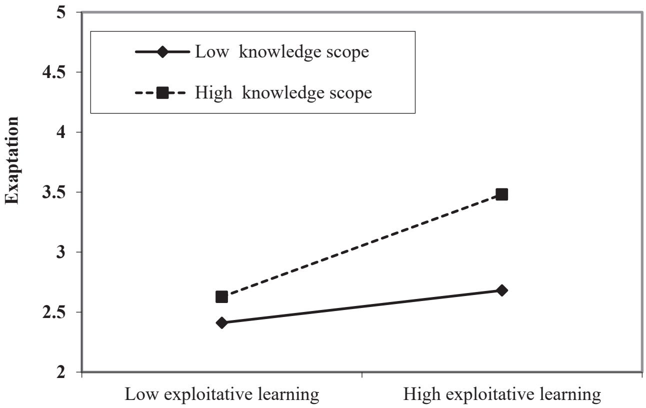

Figure 3. Moderating effect of knowledge scope on the relationship between exploitative learning and exaptation

exaptation became stronger with the increase in the KS, which had a stronger effect than that with the narrow KS.

As displayed in Figure 4, under various KRA levels, exploratory learning and exaptation exhibited a differentiated relationship. When KRA was at a low level, exploratory learning was positive but not significantly correlated with exaptation ($t = 1.049$, $p > 0.1$). When KRA was high level, exploratory learning was positively correlated with exaptation ($t = 4.196$, $p < 0.001$), which revealed that a high level of KRA could significantly enhance the positive effect of exploratory learning on exaptation, whereas a low level of KRA did not have any positive effect. As displayed in Figure 5, at various KRA levels, exploitative learning and exaptation were both positively related. However, the slope of the straight line was smaller ($t = 3.104$, $p < 0.01$) at low KRA levels, and the slope of the straight line was larger ($t = 5.782$, $p < 0.001$) at high KRA levels, which indicated that high KRA could enhance the role of exploitative learning in promoting exaptation. Furthermore, this condition was more significant than the moderating role of low-level KRA.

Table 8 further examines the joint moderating effect of KS and KRA on dual learning and exaptation. Model 2 in Table 6 shows that the interaction between KS and KRA has a

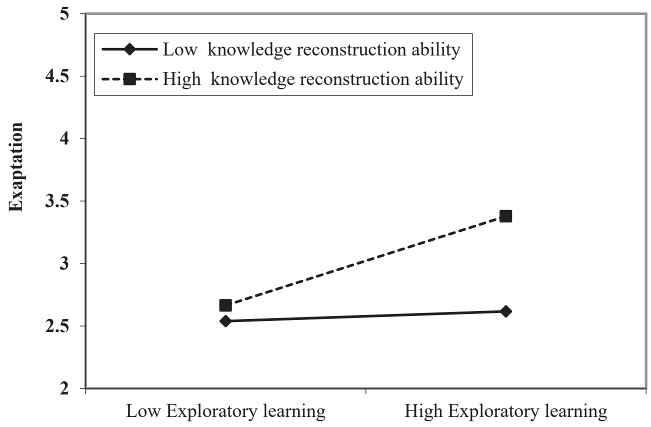

Figure 4. Moderating effect of reconstruction knowledge ability on the relationship between exploratory learning and exaptation

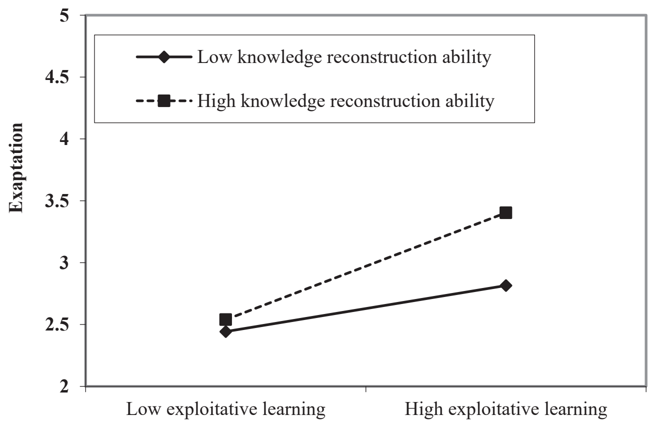

Figure 5. Moderating effect of reconstruction knowledge ability on the relationship between exploitative learning and exaptation

significant positive moderating effect on exploratory learning and exaptation (β = 0.220, $p < 0.05$), and hypothesis 7 holds true. The hypothesis that the interaction between KS and KRA has a significant positive moderating effect on exploitative learning and exaptation in Model 4 of Table 8 is not significant ($\beta = -0.052$, $p > 0.05$), and Hypothesis 8 is not supported. Figure 6 shows that when the interaction between KS and KRA is at a low level, exploratory learning is positively correlated with exaptation but not significant ($t = 0.096$, $p > 0.1$); when the interaction between KS and KRA is at a high level, exploratory learning is significantly positively correlated with exaptation ($t = 2.641$, $p < 0.01$), indicating that the larger the interaction between KS and KRA, the stronger the positive promotion effect of exploratory learning on exaptation, further verifying hypothesis 7.

4.4 Cross-industry robustness test

First, we conducted a moderation analysis by adding interaction terms between industry type and AL (i.e. exploratory learning and exploitative learning). As shown in Table 9, neither the

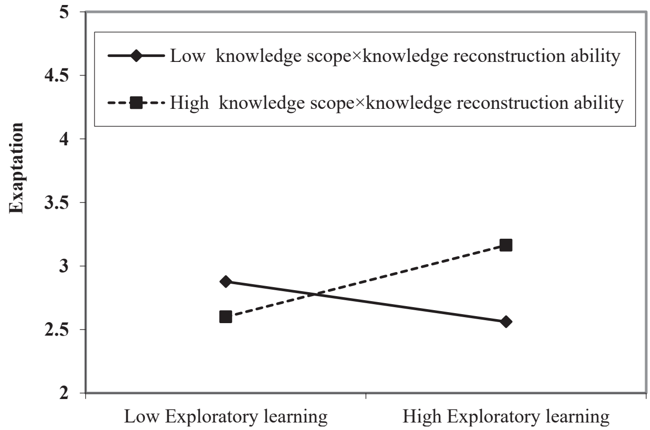

Figure 6. Moderating effect of the interaction between knowledge scope and knowledge reconstruction ability on the relationship between exploratory learning and exaptation

Table 8. The moderation test of the interaction between knowledge scope and knowledge reconstruction ability on ambidextrous learning and exaptation

Variable	Exaptation M1	M2	M3	M4
Firm age	−0.067	−0.060	−0.053	−0.057
Firm scale	0.009	0.007	−0.004	−0.009
Ownership	0.004	−0.003	−0.073	−0.075
Industry	−0.078	−0.074	0.015	0.014
EL_1	0.112	0.062		
EL_2			0.252***	0.270***
KS	0.302***	0.277***	0.229***	0.249***
KRA	0.146*	0.124	0.106	0.124*
EL_1 × KS	0.123	0.121		
EL_1 × KRA	0.107	0.183*		
KS × KRA		0.081		0.082
EL_2 × KS			0.116	0.068
EL_2 × KRA			0.073	0.056
EL_1 × KS × KRA		0.220*		
EL_2 × KS × KRA				−0.052
$\triangle R^2$	0.161	0.170	0.210	0.216
F	8.550***	7.568***	10.141***	8.590***

Table 9. The moderating effect of industry on ambidextrous learning-exaptation relationships

Moderating variable	Independent variable	Dependent variable	P	LLCI	ULCI
Industry	exploratory learning	exaptation	0.345	−0.248	0.087
Industry	exploitative learning	exaptation	0.948	−0.158	0.169

Note(s): LLCI = Lower Limit of Confidence Interval; ULCI = Upper Limit of Confidence Interval exploratory learning × industry interaction nor the exploitative learning × industry interaction was significant ($p > 0.10$), suggesting that the effects of AL do not vary significantly across industries.

Second, we performed subsample analyses by dividing the full sample into five industries: textile and apparel, furniture, food processing, pharmaceutical manufacturing, and others. Regression results (Table 10) consistently supported the main hypothesis in all subsamples. Notably, the textile and apparel subsample ($n < 30$) showed slightly weaker statistical power, with exploratory learning positively correlated with exaptation ($\beta = 0.325$, $p < 0.1$) and exploitative learning having a marginally significant effect ($\beta = 0.432$, $p < 0.05$). These results further validate the cross-industry generalizability of our core conclusions.

5. Discussion

5.1 Main findings

This study examines the relationship between AL and exaptation, exploring the moderating roles of KS and KRA. Based on data from 354 Chinese firms, our results reveal two key findings. First, we find that both exploratory and exploitative learning have a positive impact on exaptation through dual mechanisms: exploratory learning contributes by acquiring new technologies and markets, thereby establishing both knowledge reservoirs and implementation conditions for novel functionalities of existing technologies in new domains; simultaneously, exploitative learning enhances exaptation likelihood through refining, extending, improving, and transforming established technologies to generate new functions or adapt them to novel environments. These results align with prior research on AL and specific types of innovation. Duan and Gu (2021) suggested that AL can enhance new product innovation, while Huang *et al.* (2020) explored the effect of AL on eco-innovation, and Cao *et al.* (2019), Cheng *et al.* (2024) revealed the relationship between AL and firm innovation. Our study extends these findings by demonstrating the positive effect of both exploratory and exploitative learning on exaptation.

Second, we find that KS moderates the relationship between AL and exaptation, consistent with previous research demonstrating KS's amplification effect on innovation performance through knowledge acquisition (Chung *et al.*, 2018; Li *et al.*, 2021a,b,c; Wang *et al.*, 2024a, b). Specifically, broader knowledge scopes expand domain coverage, thereby enhancing AL's capacity to foster exaptation. Additionally, our study shows that KRA significantly moderates the effects of AL on exaptation, consistent with previous research on the moderating role of KRA in the formation of innovation performance (Wang *et al.*, 2023). This is because stronger reconstruction ability facilitates internal-external knowledge integration and novel function identification. Crucially, the interaction between KS and reconstruction ability positively

Table 10. Robustness test of different industry main assumptions

Industry	Main hypothesis	β	Sig.	*p*	Sample size
Textile and apparel	EL_1→EXAP	0.325	0.092	1.751	28
	EL_2→EXAP	0.432	0.022	2.442	28
Furniture	EL_1→EXAP	0.318	0.009	2.704	67
	EL_2→EXAP	0.304	0.012	2.571	67
Food processing	EL_1→EXAP	0.283	0.006	2.831	94
	EL_2→EXAP	0.381	0.000	3.948	94
Pharmaceutical manufacturing	EL_1→EXAP	0.369	0.000	4.282	118
	EL_2→EXAP	0.277	0.002	3.104	118
Others	EL_1→EXAP	0.334	0.022	2.380	47
	EL_2→EXAP	0.329	0.024	2.334	47

moderates the relationship between exploratory learning and exaptation by simultaneously providing strategic foresight while establishing knowledge integration foundations. However, this synergistic effect proves insignificant for exploitative learning-exaptation relationships, potentially due to firms' failure to develop integrated mechanisms that combine exploitative learning with KS and reconstruction ability for optimal exaptation outcomes.

5.2 Theoretical implications

This study contributes to the theoretical literature in several ways. First, it advances AL research by establishing its connection with exaptation—an underexplored innovation mechanism critical for technological evolution (Gould and Vrba, 1982; Ren *et al.*, 2019). While existing studies have extensively documented AL's impacts on conventional innovation outcomes, including disruptive innovation (Yang, 2024), product innovation (Duan and Gu, 2021), innovation performance (Cao *et al.*, 2019; Huang *et al.*, 2020), and sustainability metrics (Lv *et al.*, 2021), its role in enabling exaptation remained theoretically underdeveloped. Our findings bridge this gap through empirical validation of AL's exaptation facilitation mechanisms, thereby expanding the theoretical boundaries in organizational learning research.

Second, this study advances the exaptation literature by identifying AL as a novel driver through based on organizational learning theory. While prior research has established exaptation's cross-industry significance (Ren *et al.*, 2019; Liu *et al.*, 2021; Li *et al.*, 2022) and identified key antecedents—including product-environment-user interactions (Andriani *et al.*, 2017), cross-domain knowledge integration (Perry-Smith and Mannucci, 2017), knowledge heterogeneity (Dew *et al.*, 2004; Abatecola *et al.*, 2016), and customer-driven innovation (Andriani *et al.*, 2017; Tang *et al.*, 2022a, b)—existing studies inadequately address systematic knowledge acquisition mechanisms. We bridge this gap by demonstrating how AL synergistically integrates exploratory learning's knowledge-reservoir development for novel applications (McCarthy *et al.*, 2017) with exploitative learning's capability for functional augmentation and environmental adaptation (Levinthal and March, 1993), thereby proposing a more holistic exaptation framework that transcends prior fragmented approaches.

Third, this study advances theoretical understanding by identifying KS and reconstruction ability as critical moderators of the AL-exaptation relationship. Grounded in the knowledge-based view, we demonstrate how broader KS amplifies this linkage, extending prior work on its role in network innovation (Men and Lan, 2023) and brokerage dynamics (Rong *et al.*, 2024). From a dynamic capabilities perspective, we reconceptualize KRA as a significant enhancer (versus its traditional framing as a mediator/predictor in Ye *et al.*, 2016; Marinelli *et al.*, 2024; Luo *et al.*, 2024). Crucially, we uncover a synergistic moderating effect when KS interacts with reconstruction capability, with particularly pronounced effects in exploratory learning contexts. These findings respond to Wang and Zhao's (2023) call for boundary condition investigations while providing a nuanced framework explaining how organizational knowledge architectures shape exaptation outcomes.

Fourth, this study makes significant theoretical contributions by developing a dual-path framework of exaptation generation through synthesizing knowledge ecosystems, organizational learning theory, knowledge-based view, and dynamic capabilities theory. Meanwhile, drawing on Caputo (2024) research, we identify two distinct patterns: (1) The "outside-in" model demonstrates how exploratory learning facilitates exaptation through three sequential stages: acquiring external technological/market knowledge (McCarthy *et al.*, 2017), integrating this knowledge with existing systems through KS and reconstruction capability, and ultimately generating either extra-use exaptation (Weible, 2013) or scenario-driven exaptation (Andriani and Carignani, 2014), as shown in Figure 7. (2) Conversely, the "inside-out" model reveals how exploitative learning transforms existing technologies via refinement and extension, which then adapt to new environments through KS-enabled diversification (Luo, 2009) or capability-driven recombination (Levinthal and March, 1993).

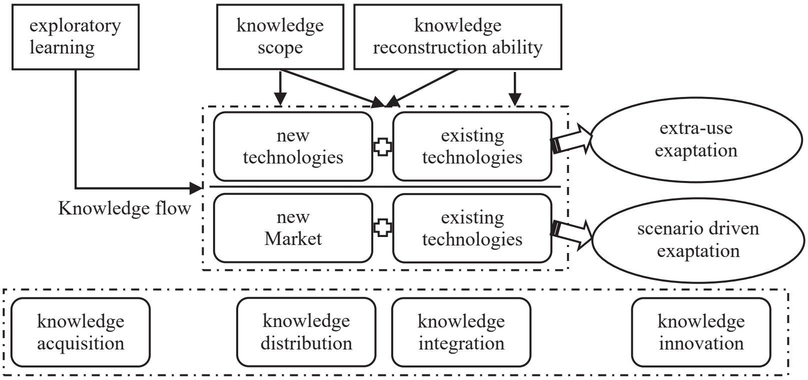

Figure 7. Exploratory learning-driven exaptation based on ecosystem theory

By integrating these theoretical perspectives, we provide the first comprehensive framework that systematically explains exaptation generation mechanisms, significantly advancing beyond previous partial examinations of antecedent factors, as shown in Figure 8.

5.3 Practical implications

First, this study provides a dual-path framework for manufacturing exaptation, addressing prior overemphasis on isolated factors like M&A or organizational culture (Dew *et al.*, 2004; Andriani *et al.*, 2017). By integrating AL, KS, and reconstruction ability, firms can sustain serendipitous discoveries and contextualize them into exaptation (Abatecola *et al.*, 2016). This synergy enables two behavioral logics: (1) Inside-out: Leveraging internal knowledge systems to repurpose technologies (e.g. adapting automotive battery tech for energy storage). (2) Outside-in: Absorbing external insights to redefine existing patents (e.g. applying AI-driven data from smart factories to optimize logistics). Both approaches resolve the “function transfer” challenge while building low-cost innovation pathways (Ren *et al.*, 2019).

Second, the framework tackles dormant patent issues plaguing Chinese manufacturers (Yuan, 2009; Nie *et al.*, 2024). Key strategies include: (1) Cross-boundary collaboration: Utilize industry-university partnerships or tech exhibitions to diversify knowledge interactions, activating dormant patents through unexpected combinations (Garud *et al.*, 2018).

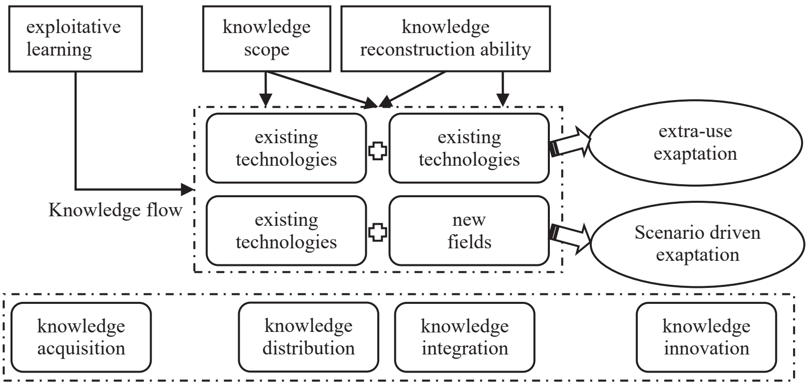

Figure 8. Exploitative learning-driven exaptation based on ecosystem theory

(2) Ecosystem building: Engage users, communities, and institutions to create inspiration-rich scenarios (Baldwin and von Hippel, 2011). For instance, open innovation platforms stimulate collective inspiration, creativity, and imagination, ultimately facilitating the discovery of new applications for 'sleeping patents' through contextual exploration (Nie *et al.*, 2024). (3) Knowledge restructuring: Bridge external knowledge with internal systems to unlock novel applications (Ye *et al.*, 2016). Procter and Gamble's "Connect + Develop" program exemplifies this, transforming dormant patents into market-ready products via external partnerships (Huston and Sakkab, 2006).

5.4 Limitations and future directions

This study has several limitations. First, while it examines the impact of AL (exploratory and exploitative learning) on exaptation, complex internal dynamics—such as how exploratory learning influences exploitative learning, and their complementary or synergistic relationships (Yi *et al.*, 2018)—remain underexplored and warrant future investigation. Second, AL may indirectly drive exaptation through mediating mechanisms like cross-border search or dynamic capabilities. Future studies should test these pathways to clarify causal linkages. Third, the use of cross-sectional data limits insights into temporal dynamics. Since AL effects and exaptation often unfold over time, longitudinal designs are needed to rigorously establish causality (Wang *et al.*, 2012). Fourth, the study of exaptation offers significant potential for expansion in terms of research methodologies and contexts (Ren *et al.*, 2019). Methodologically, prior research on exaptation has predominantly relied on qualitative approaches, with a notable lack of empirical studies. Andriani *et al.* (2017) proposed an alternative method for measuring exaptation by analyzing user-driven deviations from original functions using secondary data (e.g. DrugDex, ICD-9-CM), providing a theoretical foundation for exaptation measurement in specific industries such as pharmaceuticals. However, cross-industry measurement of exaptation remains an unresolved challenge. Tang *et al.* (2022a, b) and Wang and Zhao (2023) conducted empirical studies on exaptation using scale-based methods, offering another viable approach for its measurement. Nevertheless, research on exaptation scales is still in its infancy and requires further systematic exploration by scholars to enrich the methodological toolkit (Ren *et al.*, 2019; Wang and Zhao, 2023). In terms of research contexts, exaptation can be examined across diverse industries and cultural settings (Ren *et al.*, 2019). On one hand, prior studies have largely focused on qualitative analyses within specific industries, making cross-industry empirical research a promising direction. On the other hand, most existing research has been conducted in Western developed countries, highlighting the importance of exploring exaptation in the context of Eastern developing nations. Finally, while common method bias was mitigated through questionnaire design (e.g. anonymization and reverse-coding), self-reported data inherently carry subjectivity (Zhu *et al.*, 2024). Complementing surveys with qualitative methods—such as case studies or expert interviews—could strengthen methodological robustness.

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