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Research on the Impact Mechanism of Cross-Border Integration Ability of Entrepreneurial Teams on the Growth Performance of New Enterprises

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ABSTRACT Entrepreneurial teams often possess diverse cross-industry resources, but insufficient integration capability can lead to resource dispersion and weaken the growth performance of new enterprises. To explain how cross-industry integration capability is transformed into growth outcomes, this study adopts a mixed experimental design combining scenario simulation and quasi-natural experiment. First, a scenario simulation experiment is used to examine the causal effect of cross-industry integration capability on resource-assembly behavior under controlled conditions. Second, a quasi-natural experiment based on industry policy shocks is used to analyze how capability differences affect long-term firm performance in real business environments. The results show that high cross-industry integration capability significantly improves resource-assembly levels, with Cohen's d ranging from 0.89 to 1.24, and enhances growth resilience under external shocks. The study indicates that cross-industry integration capability is a trainable and observable dynamic capability. The mixed experimental design connects micro-level resource interaction with macro-level growth performance, providing theoretical and practical support for entrepreneurial team capability development and new enterprise growth.

INDEX TERMS entrepreneurial teams, cross-industry integration, resource assembly, growth performance, dynamic capability

I. INTRODUCTION

As innovation-driven development strategies continue to evolve, entrepreneurial teams with diverse knowledge backgrounds have become a key force in advancing high-performance research and fostering the development of new enterprises. This interdisciplinary synergy is essential for integrating advanced material science and digital technologies into the evolution of the modern industry [1]. However, a key tension exists in practice: although teams possess cross-domain resources, they often suffer from "dormant" or "dissipated" resources due to insufficient integration efficiency, making it difficult to transform these resources into sustainable growth drivers for enterprises. This phenomenon highlights the importance and urgency of shifting from static focus on "what resources are available" to dynamic exploration of "how capabilities can integrate resources" [2,3]. Existing literature has extensively examined the impact of structural factors such as team heterogeneity and social networks on the performance of new enterprises, and some studies have also touched upon concepts such as cross-domain learning and resource integration. Recent advances by Dulal et al. demonstrate how the integration of nanomaterials, electronic engineering, and manufacturing can create innovative, high-performance products that balance functionality and environmental benefits [4]. Amjad and Joshi [5] recently provided a comprehensive review of technological advancements in the industry, examining how artificial intelligence is transforming material development, machine manufacturing processes, and stakeholder experiences. Zdravković et al. reviewed the application of artificial intelligence in various business modules of manufacturing enterprises from the perspective of enterprise information system architecture, and pointed out that it is integrating with technologies such as industrial Internet of Things, distributed systems, and cloud computing to promote the transformation of enterprises towards intelligence [6]. Li et al., based on the socio-technical perspective, constructed a theoretical framework to explain how information technology capabilities and knowledge processes synergistically promote the digital business transformation of enterprises through empirical analysis of Indonesian enterprises [7]. Sheng and Saide, based on the feasible system model and combined with empirical data from multiple industries in Indonesia, constructed and verified the mechanism model of the synergistic effect of virtual enterprises, big data and knowledge dual capabilities on the viability of the supply chain, and pointed out that knowledge exploration and utilization play a key mediating role in the crisis through enterprise virtualization transformation and data analysis [8]. However, most of these studies regard cross-border integration capabilities as a "black box" or simply equate them with background diversity, lacking a micro-deconstruction of their internal behavioral dimensions and dynamic transformation processes, and failing to systematically reveal the specific path and situational conditions that affect performance, resulting in limited theoretical explanatory power and practical guidance. To overcome these limitations, this study adopts a hybrid experimental design that combines micro-behavioral experiments with macro-level quasi-natural experiments. This approach helps unpack the mechanism linking capability development to performance outcomes. At the theoretical framework level, to transform the abstract concept of "cross-disciplinary integration capability" into an observable and analyzable operational construct, we deconstructed it into three key behavioral dimensions based on literature review and preliminary research. It is crucial to emphasize a clear conceptual distinction: these dimensions represent the underlying capability itself—the potential for certain behaviors—not the behavioral outcomes. In the subsequent experimental design, capability is operationalized as a stable team characteristic measured prior to the task (through background assessment and pre-task surveys), while the dependent variables—resource linkage breadth, solution innovativeness, and conflict resolution efficiency—are measured as distinct behavioral outcomes during task execution. This temporal and conceptual separation avoids tautology by ensuring that capability (predictor) and resource bricolage behaviors (outcomes) are empirically distinct constructs. This study aims to systematically reveal the intrinsic mechanisms and boundary conditions by which the cross-industry integration capabilities of entrepreneurial teams influence the growth performance of new enterprises. To this end, firstly, a situational simulation experiment is conducted to accurately examine the causal effect of capability on resource aggregation behavior in a controlled environment; then, using the exogenous event of industry policy shocks, a quasi-natural experiment is used to verify the performance value of capability in a real business environment. This methodological combination creates a coherent evidence chain from micro-behavior to macro-performance while providing a new paradigm for empirical research on dynamic capability theory within high-performance innovation. By integrating these insights, the study offers guidance with theoretical depth and practical significance for the capability building and resource management of entrepreneurial teams.

II. STRATEGIC CASE SELECTION AND THEORETICAL FRAMEWORK CONSTRUCTION

To reveal the dynamic process and contextualized mechanism by which cross-industry integration capabilities influence the growth performance of new enterprises, this study first employs a multi-case comparative research method. Case studies are particularly suitable for exploring "how" and "why" questions, enabling the capture of complex behaviors and processes that are difficult to measure through questionnaires by deeply analyzing real-world situations. In case selection, this study follows the principle of "theoretical sampling", aiming to select cases that provide the most information for theory construction. We set three core screening criteria: First, the enterprise must be in its critical growth period of 3-8 years after its establishment, during which the team's capabilities have the most significant impact on performance; second, the core entrepreneurial team must possess significant functional or industry background diversity to ensure the existence of the "cross-industry" phenomenon; third, the enterprise must have experienced at least one major strategic challenge or growth turning point to observe the dynamic application of capabilities. Based on this, we ultimately selected two eligible startups from each of the three different industries—smart hardware, emerging consumer brands, and enterprise service software—for a total of six cases, forming a small sample set for comparison [9]. At the theoretical framework level, to transform the abstract concept of "cross-disciplinary integration capability" into an observable and analyzable operational construct, we deconstructed it into three key behavioral dimensions based on literature review and preliminary research, and presupposed their potential pathways of action. These three dimensions include: information scanning and heterogeneous knowledge acquisition (focusing on how teams proactively search for and absorb information from different fields such as technology, market, and users); knowledge translation and collaborative reconstruction (focusing on how teams "translate" and integrate the professional knowledge of members from different backgrounds to form consensus solutions); and conflict coordination and strategic decision-making (focusing on how teams coordinate and make final strategic choices when facing cognitive conflicts). This preliminary framework is not used to test hypotheses, but rather as a "sensitized concept" to guide subsequent data collection and analysis, helping researchers focus on the phenomena most relevant to the research question from a vast amount of field data.

III. MULTI-SOURCE DATA ACQUISITION AND TRIANGULATION

To ensure the reliability, richness, and accuracy of the research findings, this study adopted a multi-source data collection strategy and systematically triangulated key information. Data collection focused on the core founding teams and key development events of each case study company, lasting approximately eight months. The data primarily came from three sources: First, multiple rounds of semi-structured in-depth interviews were conducted. Interviews are the core method for obtaining firsthand information on the team's internal cognitive and behavioral processes. We conducted at least two rounds of interviews with the founder and 2-3 core members of each case study company, completing a total of 38 effective interviews. The interview outlines were designed around a pre-set theoretical framework but remained open and flexible. The first round of interviews focused on a panoramic understanding of the company's development history, team composition, and key challenges faced. Based on this, the second round of interviews focused on 1-2 specific key decision-making events (such as new product direction decisions or core crisis responses), delving into the details of interactions among team members at the time of the event, the points of disagreement, the integration process, and the final decision-making logic, in order to capture the dynamic performance of cross-disciplinary integration capabilities. Second, archival materials and text records were systematically collected and analyzed. To supplement potential biases in retrospective statements from interviews, we extensively collected internal archives and external text materials related to key events. Internal materials included iterative versions of the business plan, project meeting minutes, anonymized internal emails, and organizational charts. External materials covered publicly available reports on the company's development history, industry analysis reports, founders' public speeches, and patent documents. These archival materials provided "immediate" evidence at the time of events, facilitating cross-validation of interview content over time and supplementing objective details in team interactions that were not actively mentioned by interviewees [10]. Finally, limited participatory observation was conducted. Where possible, researchers were allowed to attend nine strategic workshops or project debriefing meetings at some of the case study companies. This non-participatory observation aimed to directly capture the team's real-time communication patterns, language habits, and informal interactions when facing real problems, providing a vivid behavioral footnote to understanding the abstract dimension of "knowledge translation and collaborative reconstruction". To enhance the construct validity and internal validity of the research, we conducted rigorous triangulation of the three types of data. Specifically, for the same key event, we cross-referenced descriptions from multiple parties in the interviews, formal decision-making texts recorded in the archives, and on-site records in the observation notes. If inconsistencies are found in the narratives, clarification and confirmation will be achieved through follow-up questioning or supplementary information. This process not only helps verify the facts themselves but also reveals the diverse perspectives and cognitive differences that may be implied behind different information, thus providing a more comprehensive and realistic portrayal of the complex context in which cross-industry integration occurs. This study was approved by the Ethics Committee of Hunan Railway Professional Technology College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

IV. CROSS-CASE ANALYSIS PROCESS AND MECHANISM EXTRACTION

First, in-depth case-specific analysis is conducted. We have established independent analysis files for each case company. The analysis focuses on the key growth events identified in the early stages, using a chronological narrative method to detail the three stages of event development: the challenge origin and information input stage, the team internal discussion and integration process stage, and the final decision-making and performance output stage. During this process, we pay particular attention to and encode the team's specific behavioral performance in three pre-defined dimensions (information scanning, knowledge translation, and conflict coordination), while tracking how these behaviors trigger the reconstruction of resources and cognition (i.e., the resource piecing process), and ultimately link them to observable performance results (such as successful product launch, changes in market share, and breakthroughs in financing). This step transforms the complex raw data into a structured "storyline", laying the foundation for subsequent comparisons [11]. Second, structured cross-case comparisons are implemented. We presented the structured storylines of six cases side-by-side for a systematic comparison. The core objective of this comparison was to identify the key behavioral patterns and contextual conditions leading to performance differences. We created a large cross-analysis matrix, visually arranging each case's performance across key dimensions, the industry and resource contexts they faced, and their final performance. Through repeated comparisons, two clear patterns gradually emerged: high-growth performance cases generally exhibited a "proactive-strategic" integration pattern, meaning the teams proactively scanned cross-disciplinary information, consciously constructed a shared cognitive framework to translate expertise, and guided cognitive conflicts into constructive debates; while low-growth performance cases mostly presented a "passive-coping" pattern, with their integration behaviors often being reactive and fragmented, and prone to stalemates or compromises in conflicts. Through further abstraction and integration of the common patterns in the six cases, this paper constructs a core mechanism model of "cross-disciplinary integration capability—contextualized resource bricolage—new corporate growth performance", to systematically explain how capabilities are transformed into corporate growth results through specific behavioral processes. As shown in Figure 1, the model reveals that cross-border integration capabilities do not directly affect performance, but rather promote the formation of competitive advantages and adaptive growth resilience by driving the key mediating process of contextualized resource bricolage.

These process vignettes reveal two distinct transformation

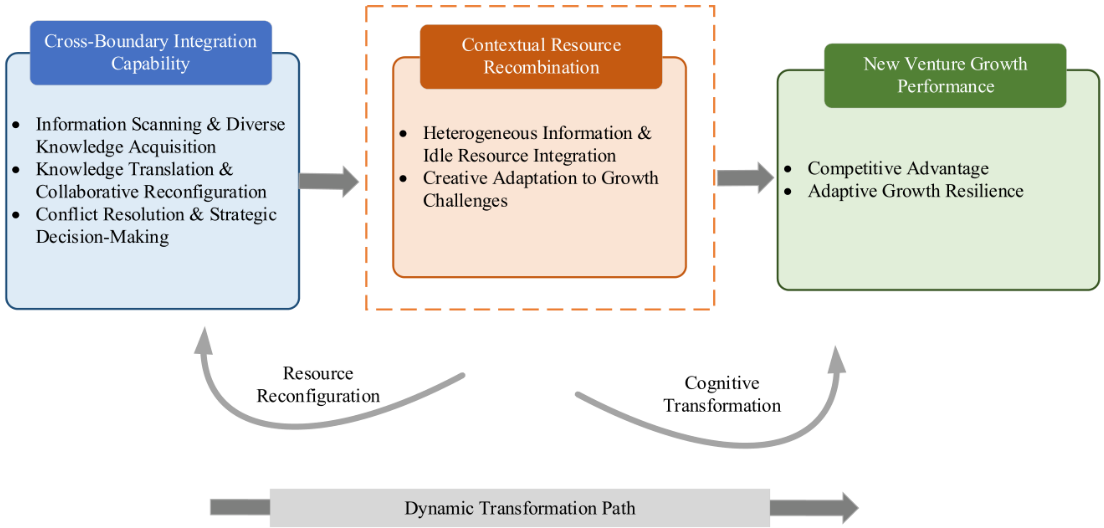

FIGURE 1. Core Mechanism Model of Cross-Industry Integration Capability Affecting the Growth Performance of New Enterprises

pathways. First, cognitive transformation occurs through what we term "conceptual bridging events"—moments when team members explicitly negotiate and reconcile divergent mental models, resulting in shared cognitive frameworks that persist beyond the immediate interaction. Second, resource reconfiguration manifests as "asset repurposing sequences", where teams identify and redeploy underutilized or dormant resources (technical, financial, or human) in response to strategic challenges. These granular observations, triangulated across interview, archival, and observational data, transform the abstract mediators in Figure 1 into empirically observable processes, thereby revealing the underlying mechanism of how integration capabilities translate into growth performance.

V. RESEARCH VALIDITY AND THEORY CONSTRUCTION ASSESSMENT

A. OVERALL EXPERIMENTAL SETUP

To systematically test the theoretical mechanism initially constructed from the multi-case study and assess its internal and external validity, this study adopted a hybrid verification strategy combining control experiments and quasi-natural experiments. This strategy aims to provide progressive and comprehensive empirical support for the core logical chain of "cross-border integration ability → resource bricolage behavior → adaptive growth of new enterprises" from two levels: "micro-behavioral causality" and "macro-performance effect".

B. CAUSAL MECHANISM TESTING EXPERIMENT BASED ON CONTEXTUAL SIMULATION

The experimental manipulation was refined to distinguish between capability activation and simple instruction-following. Instead of providing step-by-step directives, the experimental group received a structured facilitation framework that prompted them to reflect on their diverse knowledge backgrounds and consciously apply integration heuristics to the task. The control group participated in an equivalent-duration placebo activity involving general team-building discussions unrelated to cross-boundary integration, thereby controlling for the Hawthorne effect. Both groups worked under identical task conditions and resource constraints. Participants ($N = 160$) were randomly assigned to 40 four-person teams. These 40 teams were then randomly allocated to experimental and control conditions, with 20 teams (80 participants) in the experimental group and 20 teams (80 participants) in the control group. This sample size per condition ($n = 20$ teams) exceeds the minimum threshold recommended for detecting large effects ($d = 0.8$) with 80% power at $\alpha = 0.05$ in a two-sample t-test (minimum required = 15 teams per group), ensuring sufficient statistical power for our analyses. To ensure baseline comparability, we collected demographic data on all participants prior to the experiment. Independent samples t-tests confirmed no significant differences between groups in age ($M\_exp = 27.3$ years, $M\_ctrl = 27.1$ years, $p = 0.82$), educational attainment ($p = 0.71$), industry background distribution ($p = 0.64$), or prior entrepreneurial experience ($p = 0.58$). Critically, the proportion of participants with previous startup founding experience was balanced (experimental group: 18.8%, control group: 17.5%, $\chi^2 = 0.04$, $p = 0.84$), ensuring that observed performance differences cannot be attributed to pre-existing entrepreneurial capabilities. These variables were also included as covariates in subsequent analyses, with results remaining robust. As shown in Figure 2:

Figure 2(a) shows the box plot comparing the distribution of teams with high and low cross-boundary integration capabilities across the three dimensions of resource bricolage; Figure 2(b) clearly presents the differences in mean and standard deviation between the two groups in the corresponding dimensions. The experimental group significantly

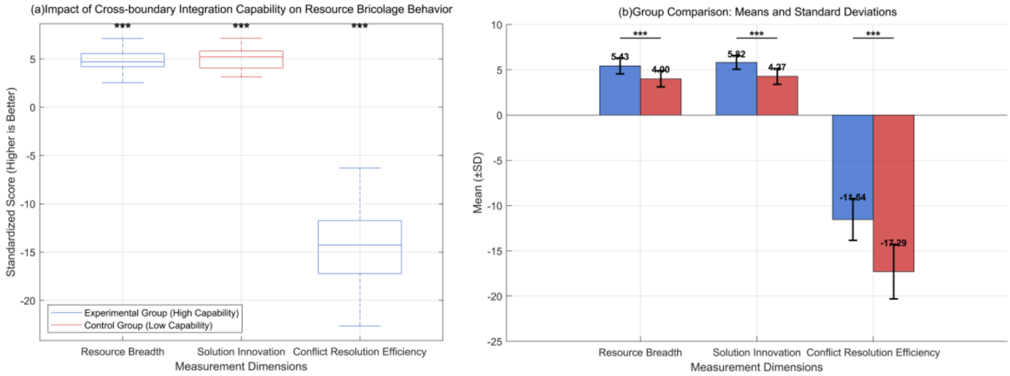

FIGURE 2. Causal mechanism testing and evaluation based on scenario simulation. Note:*** indicates significant differences between groups at p<0.001.

outperformed the control group in all three dimensions: breadth of resource linkage ($M = 5.43$ vs 4.00, $t = 4.76$, $p < 0.001$, $d = 0.89$), innovativeness of solutions ($M = 5.82$ vs 4.27, $t = 5.43$, $p < 0.001$, $d = 1.24$), and efficiency in conflict resolution (time 11.5 min vs 17.3 min, $t = 5.88$, $p < 0.001$, $d = 1.05$), with effect sizes reaching the large effect level. The experimental results strongly support the causal path of "capability $\rightarrow$ behavior" and provide an empirical basis for research on the influencing mechanism. It's important to note that the "conflict resolution efficiency" measured in the experiment (11.5 minutes vs. 17.3 minutes) doesn't merely represent time savings. In real-world startup scenarios, this efficiency metric is a visible indicator of the quality of team cognitive integration. Efficient conflict resolution means the team can reach a consensus on technology roadmaps and market strategies more quickly, thereby reducing "decision delay costs" caused by internal friction during resource allocation. This efficient interaction process directly translates into faster new product development (such as the number of new products launched in Section External Validity Verification Experiment Based on Quasi-Natural Experiment) and sends a positive signal to external investors that the team is functioning well and has strong execution capabilities. In the information-asymmetric early-stage funding market, this signaling ability is a key non-financial factor influencing the amount of funding, thus linking the minute differences in the lab to real-world funding outcomes.

C. EXTERNAL VALIDITY VERIFICATION EXPERIMENT BASED ON QUASI-NATURAL EXPERIMENT

This study employed a quasi-natural experiment design, using the paradigm shift in the fintech industry triggered by the implementation of new data security regulations as an exogenous shock. Startups established for 3–8 years with publicly available data were selected as the initial sample. To mitigate survivorship and hindsight bias in capability measurement, we adopted a two-pronged approach. First, capability assessment was strictly restricted to information available prior to the policy shock window (i.e., using only patents filed and public statements made in the 24 months preceding the regulation implementation). This ensures that the measurement of "pre-shock capability" is not contaminated by post-shock performance outcomes. Second, we explicitly coded and retained firms that ultimately failed or exited during the observation period, classifying them based on their pre-shock documentation whenever such records existed. This approach ensures that our sample includes both "survivors" and "non-survivors", preventing the overrepresentation of successful firms that characterizes classic survivorship bias. Furthermore, we conducted a Heckman two-stage selection correction to test for potential sample selection bias arising from public documentation availability; the inverse Mills ratio was not significant ($\lambda = 0.23$, $p > 0.10$), indicating that selection based on public records does not systematically bias our capability effect estimates. Based on their cross-industry integration capabilities demonstrated before the policy implementation (retrospectively measured through textual analysis of patents, team background, and public statements), firms were divided into high-capability and low-capability groups. To control for macroeconomic confounding between 2021 and 2026, we employed a temporal cohort matching strategy. Firms were paired based on their funding-seeking timing, ensuring comparisons between firms operating within identical quarterly macroeconomic windows. Additionally, we calculated a relative financing performance index by benchmarking each firm's raised capital against the industry average for the same quarter, isolating team-specific capability effects from general economic tides. Details are shown in Table 1.

TABLE 1. External Validity Validation Assessment Based on Quasi-Natural Experiment

Group & Period	New Product Launch Speed (units/year)	New Financing Raised (Million CNY)	New Partners Added (units)
High-Capability Group (Pre-Shock)	1.8	15.2	2.5
High-Capability Group (Post-Shock)	3.2	32.5	5.1
Low-Capability Group (Pre-Shock)	1.7	14.8	2.4
Low-Capability Group (Post-Shock)	2.1	18.3	3
Difference-in-Differences Estimate (DID)	+1.0**	+11.2***	+1.6*

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

As a robustness check, financing trend analysis revealed that while both groups experienced cyclical downturns, the high-capability group consistently maintained a 30%–40%

financing premium over the low-capability group within each economic phase. The DID estimate (+ 11.2 million CNY, $p < 0.001$) represents the average treatment effect after stripping away time-fixed effects, confirming that the financing advantage stems from intrinsic team capabilities rather than fortuitous economic timing. The results show that teams with high cross-industry integration capabilities exhibit significant adaptive growth advantages when facing regulatory shocks. This confirms that cross-industry integration capability is a key mechanism helping startups gain growth advantage amidst environmental turbulence, strongly supporting the external validity of our theoretical model.

VI. CONCLUSION

This study verifies the mechanism by which the cross-industry integration capabilities of entrepreneurial teams enhance the growth performance of new enterprises by promoting specialized resource-assembly behavior through scenario simulation and quasi-natural experiments. By aligning interdisciplinary expertise with advanced fiber engineering requirements, the research demonstrates how effective resource synthesis drives innovation and market competitiveness within the modern sector. The conclusions show that this capability can not only be directly transformed into more efficient and creative resource integration behavior, but also significantly enhance the resilience of enterprises to external shocks, making it a key dynamic capability for startups to gain a sustainable competitive advantage. However, the research sample mainly focuses on technology-driven industries, and the generalizability of its conclusions in other traditional fields needs further testing; a gap still exists between the experimental environment and the complexity of real-world entrepreneurial scenarios. Future research could be expanded to more diverse industrial backgrounds within the advanced engineering sector, employing a longitudinal tracking design to capture the dynamic evolution of this capability throughout the lifecycle of innovative fiber-based enterprises. This approach will allow for a more comprehensive analysis of the boundary conditions governing technical development and its integration into the broader global market.

AUTHOR CONTRIBUTIONS

Conceptualization –Xiaoyan Zhang and Qian Liu; methodology – Xiaoyan Zhang and Qian Liu; investigation – Xiaoyan Zhang and Qian Liu; writing-original draft preparation – Xiaoyan Zhang and Qian Liu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

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ETHICS APPROVAL AND CONSENT TO PARTICIPATE

This study was approved by the Ethics Committee of Hunan Railway Professional Technology College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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