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Development and Evolution of Organizational Dynamic Capabilities during Digital-Intelligence Transformation—A Case Study of AiScholar

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Received: 21 November 2025, Accepted: 24 November 2025, Published: 28 November 2025

Abstract

Amidst the boom of the digital economy across the globe, one question confronts both scholars and practitioners alike: how can organisations build dynamic capabilities to achieve a successful digital-intelligence transformation? In the present work, an interpretive longitudinal case study on AiScholar, a one-stop scientific research service (SRS) platform, is performed based on the dynamic capabilities theory to investigate its decade-long journey of digital-intelligence transformation. It is revealed that successful transformation relies on a phased evolution of organizational capabilities from “operational optimization”, “integration & reconfiguration”, to “ecosystem empowerment”, with strict path dependency between each phase. Moreover, this phased evolution is driven by a dynamic combination of four mechanisms—strategic consensus guidance, experimental learning, knowledge codification, and ecosystem synergy. The integrated “phase-capability-mechanism” model proposed here unveils the intrinsic drivers of digital-intelligence transformation from a micro-process perspective, extends the application of the dynamic capabilities theory to research on digital-intelligence transformation, and provides strategic insights into the capability-building of knowledge-intensive service providers.

Keywords: Digital-Intelligence Transformation; Dynamic Capability; Capability Building; Case Study; Scientific Research Service

1. INTRODUCTION

Amid the relentless march of the global digital economy, digital-intelligence transformation has become a strategic imperative for firms to build sustainable competitive advantage. The breakthroughs in frontier technologies—from big data and artificial intelligence (AI) to blockchain—are not only reshaping the very foundations of knowledge production and dissemination but also posing grave challenges to operational and value-creation models of traditional organisations. Nowhere is this shift more apparent than in the scientific research service (SRS) sector, a quintessential knowledge-intensive industry now undergoing a pivotal transition from legacy models toward intelligent, platform-based, and ecosystem-based service paradigms.

The dynamic capabilities theory offers a powerful lens to examine digital-intelligence transformation. With a focus on high-level capabilities that allow enterprises to integrate, build, and restructure internal and external resources to keep pace with rapidly changing environments, this theory examines “what the enterprise can do”—the specific organizational and managerial processes—to achieve transformation instead of focusing on sketching the roadmaps detailing “what the enterprise should do”. Teece and other researchers innovatively break these capabilities into three micro-processes—sensing, seizing, and transforming. This theoretical prism proves particularly apt for analyzing the evolution of organizational capabilities through the complex journey of digital-intelligence transformation [1-4].

Existing studies on organizational dynamic capabilities, however, remain largely static, failing to dissect the micro-foundations and evolutionary pathways of these capabilities. In addition, theories on phased transformation often fall prey to linear, technologically deterministic assumptions, overlooking the punctuated, non-linear nature of organizational learning and the critical role of path dependence. To fill the research gap, this study performs an interpretive longitudinal single case study on AiScholar, a one-stop scientific research service (SRS) platform, to find answers to the following questions: What specific dynamic capabilities must an organization cultivate at each stage of its digital-intelligence transformation? Through what mechanisms are these capabilities constructed, and how do they leap to higher levels? And what inherent evolutionary logic governs the transitions between these different forms of capability?

The main contributions of this study are threefold: First, it extends the dynamic capabilities theory by applying it to the SRS industry, hence expanding its theoretical boundaries; Second, through a longitudinal case design, it illuminates the underlying micro-mechanisms of capability evolution and hence addresses a critical gap in a literature that has often prioritized macro-level outcomes over processual dynamics; Finally, a dynamic “phase-capability-mechanism” model is constructed to offer a novel analytical framework for understanding the complex journey of digital-intelligence transformation [5].

2. THEORETICAL FRAMEWORK & RESEARCH DESIGN

2.1. Development and Evolution of Dynamic Capabilities Theory

Since its inception, the dynamic capabilities theory has evolved into a seminal paradigm for explaining how firms build and sustain competitive edges within the domain of strategic management. It moves beyond the realm of operational capabilities, which are concerned merely with doing things right, to focus on higher-order capacities: the abilities of an organization to change itself for the future. At its core, the theory posits that organizations adapt to shifting environments through three critical, iterative processes: sensing new opportunities; seizing those opportunities; and transforming their resources to maintain their competitive edge.

Within the context of digital transformation, the dynamic capabilities theory is evolving along several new dimensions. First, data-driven decision-making has become a defining feature of dynamic capabilities, while rapidly iterative learning cycles accelerate organizational adaptation to technological shifts. Moreover, the rise of ecosystem-oriented coordination models compels firms to transcend boundaries and co-create value with external partners (Table 1) [5,6]. In recent years, scholars have paid increasing attention to the context-dependent nature of these capabilities: In knowledge-intensive services, for instance, the emphasis is on the capabilities to generate, share, and apply knowledge, the development of which will provide analytical insights into the digital-intelligence transformation of SRS providers [7-9].

Table 1. Comparison between traditional and digital-age dynamic capabilities

Dimension	Traditional Dynamic Capabilities	Dynamic Capabilities in the Digital Age
Key features	Resource integration, process optimization, linear adaptation	Data-driven, ecosystem coordination, agile iteration, value co-creation
Capability composition	Sensing, seizing, transforming	Operational optimization (process standardization), integration & reconfiguration (platformization), ecosystem empowerment (intelligentization)
Value Logic	Reactive adaptation to environmental changes to sustain competitive advantage	Proactive definition of new value networks to create ecosystem-level advantage
Knowledge Foundation	Dominated by tacit experience and organizational routines	Codification of explicit knowledge, with data assets as core production factors
Adaptation Context	General dynamic environments with incremental technological change	Exponential-change scenarios characterized by digitalization, platformization, and ecosystem evolution
Typical Carriers	Management cognition and decision-making processes	AI systems, digital platforms, cross-organizational API interfaces

2.2. Analytical Framework

To systematically analyze the evolutionary pathways of organizational dynamic capabilities in digital-intelligence transformation, this study proposes an integrated, three-dimensional “phase-capability-mechanism” analytical framework. Central to the framework is the proposition that the three dimensions—transformation stage, dynamic capability, and construction mechanism—exist in a state of symbiotic co-evolution. Specifically, the progression from informatization to digitization and then to

intelligentization forms the contextual backdrop of building capabilities. Within this context, dynamic capabilities unfold along a punctuated trajectory from operational optimization, through integration and reconfiguration, to ecosystem empowerment, with strict path dependencies governing transitions between each stage. The engine driving this capability evolution and phase-level transition is the orchestrated interplay of four core micro-mechanisms: strategic consensus guidance, experimental learning, knowledge codification, and ecosystem synergy [4].

2.3. Research Design and Methodologies

This research employs an interpretive longitudinal single-case study design, a methodology particularly suited for investigating “how” and “why” of complex, dynamic processes. AiScholar is selected for the case study because, first, the platform has undergone a complete transformation cycle from informatization to intelligentization; second, it is a representative example within the SRS industry; and third, it can provide a rich trove of both primary and secondary data.

Data collection adhered to the principle of triangulation from multiple sources [10], encompassing primary and secondary data gathered from 2014 to 2024. A systematic three-stage coding process is employed for subsequent data analysis, and a theoretical model grounded in the empirical data is constructed to ensure methodological rigor and reliability.

3. STUDY CASE FINDING: THREE-PHASE EVOLUTION OF DYNAMIC CAPABILITIES

						2024
						AiScholar included in Guangzhou's Inaugural Cohort of Data Factor Enterprises; Official establishment of the AiScholar Academic Committee; Successful Completion of the 100 th Session of AiScholar's University Charity Initiative; Invited to the U.S.-China Economic and Trade Cooperation Forum; Signed strategic cooperation agreement with China Science Daily; Official release of the "Blue Book on the Development of International Academic Conferences in China 2024".
						2022
						AiScholar officially joins international publishing associations, including COPE (Committee on Publication Ethics); Listed among Guangzhou's Top 100 reserve high-tech enterprises for IPO in 2022 & designated as a 2022 innovative SME in Guangdong; Signing Ceremony of SCUT-KEO Academic Exchange Foundation; Member of "Innovation China" Guangdong Provincial Academic Exchange Professional Service Group.
2014	2016	2018	2020	2022	2024	
The founding of Guangzhou KEO Information Technology Co., Ltd.; a dream set sail.	Dedicated to independent R&D; recognized as a "National High-Tech Enterprise".	AEIC signs strategic cooperation agreement with the "National High-Tech Association for Higher Education".	Donation to Zhong Nanshan Medical Foundation to fight against the COVID-19 pandemic; Expansion of physical presence: establishment of branches in North America; Chongqing, Xi'an, Hangzhou, Nanchang, and Nanjing.	AiScholar officially joins international publishing associations, including COPE (Committee on Publication Ethics); Listed among Guangzhou's Top 100 reserve high-tech enterprises for IPO in 2022 & designated as a 2022 innovative SME in Guangdong; Signing Ceremony of SCUT-KEO Academic Exchange Foundation; Member of "Innovation China" Guangdong Provincial Academic Exchange Professional Service Group.	AiScholar included in Guangzhou's Inaugural Cohort of Data Factor Enterprises; Official establishment of the AiScholar Academic Committee; Successful Completion of the 100 th Session of AiScholar's University Charity Initiative; Invited to the U.S.-China Economic and Trade Cooperation Forum; Signed strategic cooperation agreement with China Science Daily; Official release of the "Blue Book on the Development of International Academic Conferences in China 2024".	
2015	2017	2019	2021	2023	2025	
The brand AEIC officially launched, with its website going live.	AEIC signs long-term publishing agreements with its multiple international publishers.	AiScholar Platform (www.ais.cn) officially launched; The first branch of KEO founded in Henan.	Completed Pre-A round financing, embarking on a new chapter; Brand upgrading of AiScholar, unveiling the first branch in Henan.	Completed shareholding restructuring and officially renamed as "Guangzhou KEO Information Technology Co., Ltd."; Secures tens of millions of yuan in Series A funding; Honored as a "specialized, refined, unique, and innovative" enterprise in Guangdong province, and selected for Deloitte's List of Top 40 High-Tech High-Growth Enterprises in the Greater Bay Area, and the List of Top 20 High-Tech High-Growth Enterprises in Guangzhou; Officially designated as the first innovation base for sci-tech societies in Guangdong province and approved as a HOME Program Workstation of the Guangdong Association for Science and Technology; Established the "AiScholar Data Science and AI Laboratory" with Southern University of Science and Technology (SUSTech).	AiScholar's Hangzhou R&D Center was established in "China Data Valley"; Signs strategic cooperation agreement with Universiti Teknologi Malaysia; The founding of the "Joint Innovation Center" with Chengdu University of Information Technology; Reaches cooperation intent with Springer Nature; Forms a strategic partnership with the University of Salamanca; AiScholar facilitates multidimensional industry-academia-research collaboration between Chinese and European universities; Selected as a member of the National Data Standardization Technical Committee; Included in the List of Outstanding Cases of Digital Industrialization and Industrial Digitalization for Private Enterprises of 2024 in Guangdong.	

Figure 1. Digital-intelligence transformation milestones of AiScholar

Figure 1 displays the digital-intelligence transformation journey of AiScholar from 2014 to 2025, which visually captures the phased outcomes and progressive maturation of its capability architecture. This chronology provides the essential temporal framework for detailed analysis.

3.1. Phase I: Informatization (2014–2018) — Establishing the Foundation for Operational Optimization

This initial phase is defined by the organization's imperative to enhance operational efficiency and establish standardized protocols. The core dynamic capability cultivated during this period is the capability for operational optimization, which is specifically manifested in three critical dimensions: process standardization, data accumulation, and knowledge management.

3.1.1. Manifestations of Capabilities

By launching the Academic Exchange Information Center (AEIC), the parent firm of AiScholar achieved comprehensive informatized management of the entire academic conference process. This innovation involved not merely a technological implementation but, more significantly, the critical process of codifying implicit knowledge into explicit protocols. Specifically, the firm systematically transformed operational knowledge, including registration management, agenda generation, and notification systems, into standardized operational procedures. By 2018, it had served over a hundred international conferences, extending its reach to more than 30 provinces and municipalities across China and serving a research user base exceeding 100,000 individuals.

3.1.2. Mechanisms of Capability Development

These capabilities were developed through "knowledge codification" and "pain-point-driven experimentation." Confronting systemic inefficiencies within the SRS industry, the company strategically selected academic conference management—a core business function—as its initial proving ground and digitalized these critical workflows through mature IT solutions. This approach enabled rapid market entry and, by delivering marked improvements in both service responsiveness and quality, allowed the firm to build a formidable reputation within the academic community [11].

3.1.3. Outcomes and Limitations

The digitalization of workflows yielded marked gains in service efficiency and quality, laying a crucial foundation of user trust and data assets for subsequent transformation. However, capability development in this phase faced distinct constraints: System upgrades in this phase were the piecemeal addition of incremental modules and failed to achieve a holistic redesign of the operational architecture; meanwhile, decision-making still leaned heavily on empirical intuition, leaving the latent value of accumulated data largely untapped.

3.1.4. Analysis of Path Dependence in Phased Transition

The operational optimization capabilities forged in this phase provided the indispensable cornerstone for all subsequent transformations. The path dependence manifests in three critical legacies: (1) Data assets: The structured data accumulated through conference management informatization became the foundational capital for future data-driven decision-making and intelligent recommendation systems; (2) Process knowledge: The methodical codification and standardization of business processes created clearly-defined, modular components that enabled subsequent platform integration, thereby avoiding the predicament of untangling a Gordian knot during restructuring; (3) User trust: The established user base and reputation, built through consistent service, provided a crucial cohort of early adopters and inherent acceptance for the platform transition. Without this foundational groundwork, subsequent integration and reconfiguration would have faced prohibitive risks of data poverty, operational chaos, and user resistance [11,12].

3.2. Phase II: Digitalization (2019–2023) — The Emergence and Deepening of Integration & Reconfiguration Capabilities

Amid the dual pressure from mounting internal operational inefficiencies and intensifying external competition, AiScholar's core imperative shifted decisively toward cultivating integration and reconfiguration capabilities. This phase of transformation is characterized by three defining attributes: its systematic nature, its drive toward platformization, and its foundation in data-driven operations.

3.2.1. Manifestations of Capability Breakthrough

The launch of the AiScholar platform in August 2019 marked a profound structural shift in the firm's history of development. It made three pivotal breakthroughs: First, by integrating conference management with journal recommendation systems, it achieved automatic flow of submission data and fundamentally eliminated information silos. Second, it broke down conference operations into standardized, modular components that can be flexibly reconfigured for diverse scenarios. Finally, it established an internal operational coordination platform, championing both project transparency and the explicit codification of cross-departmental workflows.

3.2.2. Mechanism Innovation and Implementation

During this capability-building phase, the organization employed "strategic consensus guidance" to ensure unified direction in its transformation. Through initiatives like closed-door strategy workshops and company-wide surveys, it forged a shared understanding around core propositions, such as shifting from "customer relationships" to "platform user loyalty." Meanwhile, to address the organizational adaptation challenges following the platform's initial launch, it instituted multi-dimensional adjustment mechanisms, involving process resilience protocols, a service experience scoring system, and an official observation period for new deployments.

3.2.3. Transformation Performance Assessment

By 2023, the AiScholar platform achieved 97% operational stability while its core business processes reached maturity. The subsequent rollout of innovative features, including an AI peer review system and a big data-powered journal recommendation system, marked a strategic pivot from resource integration to value creation. This phase culminated in significant market recognition, with endorsements from international organizations like COPE and ACSE, establishing the firm as a benchmark for digital transformation in the SRS industry.

3.2.4. Analysis of Path Dependence in Phased Transition

The development of integration and reconfiguration capabilities is highly dependent on the operational optimization capabilities forged in the prior informatization phase. The crux of this transition lies in the systemic interconnection of previously isolated, "point-based" competencies. For instance, the platform's integration of conference management and journal submission systems is feasible only because both subsystems had already achieved internal standardization and datafication in the earlier stage. This enabled the organization to elevate its experimental learning from addressing "discrete pain points" to orchestrating "systemic architectural design." However, this phase also generated a new, consequential path dependence: the established platform data flows and standardized modules now constitute the very architectural scaffolding, and thus the inherent constraint, for future development. While this empowers the creation of ecosystem APIs and intelligent applications, it simultaneously channels and delimits the potential pathways for intelligentization [11].

3.3. Phase III: Intelligentization (2024 onwards) — Maturation and Expansion of Ecosystem Empowerment Capabilities

Propelled by the widespread adoption of large language models (LLMs), the organization's capability requirements are now transitioning toward ecosystem empowerment. This current phase is distinctly marked by three evolutionary traits: ecosystem-centric, intelligent, and global.

3.3.1. Architectural Characteristics of Capabilities

Anchored by its "AI Research Workspace," AiScholar has further evolved its capabilities by integrating four core functions—data aggregation, intelligent analytics, intelligent recommendation, and collaborative innovation—into a comprehensive, intelligent technological infrastructure. By establishing academic committees and co-founding joint innovation centers with universities, it has systematically constructed an open innovation ecosystem.

3.3.2. Exploration of Innovative Mechanisms

To address internal cognitive conflicts arising from AI adoption, AiScholar instituted a dual-track mechanism of "AI-led initial screening with mandatory human validation." Through empirical studies delineating functional boundaries, pilot results demonstrate AI's decisive efficiency advantages in standardized tasks, but meanwhile confirm human experts' irreplaceable role in complex contextual judgments [11,13].

3.3.3. Ecosystem Expansion Outcomes

Operational metrics for 2024 reveal the platform has supported over 5,200 international conferences and served more than 3 million researchers cumulatively. In a pivotal move for global expansion, AiScholar established a strategic partnership with Universiti Teknologi Malaysia in 2025, creating a regional service network across Southeast Asia, which marks its transition from a domestically proven model to global implementation.

3.3.4. Analysis of Path Dependencies in Phase Transition

The emergence of ecosystem empowerment capabilities represents an advanced evolution built upon the capabilities developed in the preceding two stages. It is critically dependent on the platform architecture constructed during the digitization phase, whose inherent openness and extensibility fundamentally determine the feasibility of ecosystem coordination. For instance, the development of the “AI Research Workspace” did not start from scratch but constituted an intelligent repackaging and open externalization of the platform’s existing data and service capacities. This way, the mechanism of strategic consensus guidance expanded beyond internal alignment to foster shared ecosystem vision-building among external partners. This progression demonstrates that the evolution of dynamic capabilities is not a simple sequence of replacements, but rather a layered, nested process where each stage reinforces the others. The successful emergence of higher-order capabilities is predicated upon the maturation and platformization of lower-order capabilities, and without this solid foundation, they risk becoming a proverbial house built on sand [14].

4. DISCUSSION AND THEORETICAL CONTRIBUTION

4.1. Theoretical Implications and Innovative Value of the Phased Evolution Model for Dynamic Capabilities

Through a longitudinal case study of AiScholar, this study constructs a three-dimensional “phase-capability-mechanism” dynamic model that deepens and extends existing theory across multiple fronts. The integrated model for phased evolution of dynamic capabilities (Figure 2) reveals the intrinsic driving mechanisms of digital-intelligence transformation. The study finds a strict sequential relationship among the three core capabilities, which form an irreversible, punctuated sequence. Any attempt to bypass foundational capabilities risks resulting in the unsupported suspension of higher-order capacities, as they would lack the necessary underpinning for stable development.

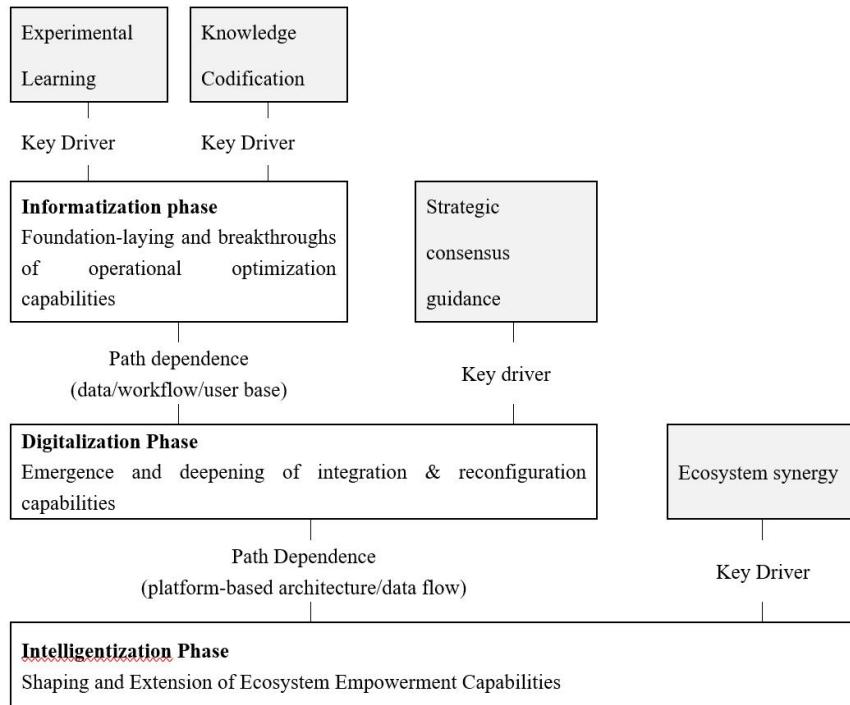


Figure 2. Driving mechanism model for dynamic capabilities development

As Figure 2 shows, the model reveals a distinct mechanism-capacity symbiosis throughout this evolution. During the informatization phase, knowledge codification and experimental learning predominated; as the organization advanced to the digitalization phase, strategic consensus guidance and structural experimentation gained prominence; finally, in the intelligentization phase, the mechanism of ecosystem synergy came to the fore. This dynamic configuration not only underscores the context-dependent nature of dynamic capabilities but also reveals that the mechanism itself is inherently dynamic and evolves with the transformation phase. This finding provides more insights into the complexities inherent in organizational learning processes [15].

4.2. Theoretical Contributions

The specific theoretical contributions of this study are threefold:

- 1) Contextual refinement: By converting the abstract concept of dynamic capabilities into a measurable chain of “operational optimization – integration & reconfiguration – ecosystem enablement,” this study extends the dynamic capabilities theory by applying it to the digital-intelligence transformation context, particularly within knowledge-intensive service enterprises [4].
- 2) Processual revelation: It uncovers the dynamic nature of capability-building mechanisms, moving beyond static descriptions to emphasize how the portfolio of mechanisms evolves with each phase of transformation. This provides a novel perspective for understanding organizational learning in digital environments [4].
- 3) Systematic supplementation: By analyzing the interaction between technological and social subsystems within the dynamic capabilities framework, the research here reveals the micro-foundations through which technological investment is successfully translated into organizational capability during digital-intelligence transformation, thereby providing a valuable extension to sociotechnical systems theory [16].

4.3. Practical Implications and Managerial Recommendations

Given the findings specified above, this study offers concrete guidance for corporate digital-intelligence transformation. First, firms need to adopt a dynamic-capabilities-oriented perspective on transformation. Corporate managers should re-examine the transformation process through the lens of capability-building and regularly audit their organization’s maturity across the three core dimensions—operational optimization, integration & reconfiguration, and ecosystem empowerment—to develop targeted improvement plans. Specifically, they can refer to AiScholar’s “Four Online” strategy—Product Online, Process Online, Customer Online, Employee Online—to establish a systematic framework for diagnosing and enhancing these critical capabilities.

Second, organizations need to sense the “rhythm” of capability-building. The research here indicates that different capabilities require distinct developmental timelines and conditions. For small and medium-sized enterprises (SMEs), the recommended strategy is “targeting key pain points and adopting an iterative, rapid-cycle approach,” prioritizing the development of operational optimization capabilities first. For established industry leaders, however, a more ambitious roadmap is necessary, involving methodical planning for integration/reconfiguration and ecosystem empowerment capabilities from the outset, leveraging strategic investments to develop higher-order capabilities. They also need to, especially in the early stages of transformation, prioritize the development of foundational capabilities to create the solid groundwork essential for all subsequent advancement.

Third, firms need to establish governance models aligned with their specific transformation phase. During the informatization stage, a relatively centralized decision-making structure may be appropriate to ensure execution efficiency. As the organization transitions to the digitalization phase, a more decentralized governance approach becomes necessary to foster organizational agility and innovation. Finally, the intelligentization stage entails the adoption of a networked governance mechanism capable of managing the complexities of ecosystem-wide development. AiScholar’s innovative institutional arrangements, such as its process resilience protocols and service experience scoring system, offer valuable references for tailoring governance to each phase of transformation.

5. CONCLUSIONS AND PROSPECT

5.1. Conclusions

Through an in-depth analysis of AiScholar's transformation journey, this study concludes that the essence of digital-intelligence transformation lies in the systematic construction and punctuated evolution of organizational dynamic capabilities—a process governed by distinct developmental pathways and evolutionary logic. Successful transformation hinges on the synergistic alignment of technological investment with capability development, the matching of strategic planning with organizational learning, and the adaptive reconciliation of internal changes with external needs.

5.2. Limitations and Future Research

This study's limitations reside in its single-case design and the inherent constraints of its data sources. Future research should pursue several promising avenues: first, conducting multi-case comparative studies to validate and refine the proposed theoretical model; second, employing mixed-methods approaches to enhance the reliability and validity of findings; and finally, dedicating specific attention to emerging challenges in intelligentization, such as algorithmic ethics and data governance.

Funding Statement: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Contribution: All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by He Wan, and Bin Xie. The first draft of the manuscript was written by He Wan and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Informed Consent Statement: Informed consent was obtained from all individual participants included in the study.

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of Interest Statement: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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