



A Dynamic Capabilities Perspective on AI-Driven Digital Upgrading of Design-Intensive SMEs

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Abstract. Driven by the explosive growth of artificial intelligence, resource-constrained small and medium-sized design organizations urgently require adaptive digital transformation pathways. Grounded in dynamic capabilities theory, this study conducts a multiple-case grounded analysis of three design SMEs to construct a "sensing-seizing-transforming" mechanism model. The findings reveal that dynamic capabilities in the AI context originate from a three-dimensional micro-mechanism: sensing capability manifests as the synergy of technological and user sensing; seizing capability involves adaptive learning and human-AI collaboration boundary governance; and transforming capability encompasses process reengineering, digital asset codification, and transformation resilience. Ultimately, this research provides a micro-process explanation and a human-AI collaborative management framework for the digital upgrading of creative organizations.

Keywords: Design-intensive SMEs; Dynamic capabilities; Human-AI collaboration; Generative AI; Grounded theory.

1 Introduction

While artificial intelligence reshapes industries, SMEs in China face severe structural constraints—such as limited resources and technical capabilities—making their digital transformation uniquely challenging [2]. Specifically, the core competitiveness of small and medium-sized creative organizations relies heavily on the tacit knowledge of individual designers, a foundation currently facing direct disruption from generative AI (AIGC). Consequently, it is crucial to systematically investigate the digital transformation trajectories and organizational capability evolution of these organizations under such technological shocks.

2 Literature Review

2.1 Digital Transformation of SMEs in the Context of AI

Generative AI is profoundly reshaping the creative industry, yet many enterprises struggle to translate technological investments into competitive advantages due to

friction with outdated organizational structures [2,12,15]. According to dynamic capability theory, organizations must continuously reconfigure resources to adapt [10]. Unlike large firms, SMEs lack redundant resources; thus, agile organizational change capabilities, rather than sheer capital investments, are crucial for them in the AI era [8]. Recent research further conceptualizes AI capability as a strategic organizational capability that must be combined with data, human expertise, routines, and resource orchestration before it can improve creativity or performance [1,9], and field evidence also suggests that AI value is uneven across tasks and depends on whether workers understand the boundary of suitable use [16]. In creative SMEs, generative AI can reshape design outputs and designers' creative thinking [6], and recent studies in fashion design further show that human-AI collaboration can support style generation, concept exploration, and early-stage design communication [17]. However, core competitiveness still relies on designers' tacit knowledge, contextual judgment, and domain-specific design experience. AI therefore presents a dual challenge: it lowers production thresholds and accelerates exploration, while also disrupting traditional mental models. This forces a systemic shift toward "human-machine symbiosis," posing an unprecedented test to the dynamic adaptive capabilities and organizational routines of creative SMEs.

2.2 Dynamic Capabilities Theory

Dynamic capabilities represent a firm's high-level ability to integrate, build, and reconfigure competences to address rapidly changing environments [10]. While existing studies highlight their mediating role in digital transformation, traditional perspectives often treat enterprises as homogeneous "black boxes," overlooking the specific process flows and agency during technology implementation. Fundamentally, dynamic capabilities comprise three dimensions: sensing capability, seizing capability and transforming capability [10].

Recent scholarship emphasizes the necessity of opening this black box by shifting the focus towards operational mechanisms [4,13]. Scholars warn that dynamic capabilities remain theoretical abstractions unless the specific organizational routines and micro-level decision rules constituting them are explicitly identified [3]. This perspective goes beyond static micro-foundations to accurately explain how the causal links, workflow reconfigurations, and dynamic feedback loops generated by multi-level actors, including management, designers, and technicians, interweave. In the context of technological adaptation, these micro-level routines serve a dual purpose: they encode existing tacit organizational knowledge while providing a platform for continuous iterative learning [11]. These mechanisms ultimately drive the entire organization to complete the dynamic evolution of "sensing-seizing-transforming." Consequently, this study focuses on a critical unanswered question: In resource-constrained creative SMEs highly reliant on tacit knowledge, how do the human-AI interaction practices of internal multi-level subjects form specific operational mechanisms across the sensing, seizing, and transforming dimensions to drive the collaborative evolution of organizational dynamic capabilities? Answering the questions will provide a systematic theoretical explanation based on dynamic capabilities

theory for understanding the digital transformation strategies of creative organizations in the AI era.

3 Research Design and Methodology

3.1 Research Design

This study adopts an exploratory multiple-case research method [14]. Since full-link AIGC application in design-intensive SMEs is still nascent, we selected three heterogeneous creative enterprises in southern China (Company A: industrial design, Company B: interaction design, and Company C: jewelry design). All these companies have substantially introduced generative AI tools for more than two years, which enhances the universality of the theory.

From October 2023 to February 2024, focusing on the core theme of "behavioral changes, cognitive adjustments, and the formation of new practices among different subjects in the process of using AI," the research team conducted multi-round, multi-role in-depth interviews with the three enterprises, and extensively collected internal technical documents and external public materials. The interviewees systematically covered the organizational management level (founders/enterprise heads), business level (technical directors/design directors/project supervisors), and individual execution level (senior designers and frontline designers) to obtain a rich contextual perspective across levels and functions. Through the mutual corroboration and triangulation of the above multi-source data [14], this study ensured the objectivity of the interview content and the credibility of the research conclusions.

3.2 Data Analysis

This study utilizes grounded theory to systematically analyze interview data and materials using MAXQDA [7]. Through continuous comparison, we conducted open coding to extract 44 initial concepts. Axial coding then synthesized these into 12 higher-level categories, which were subsequently mapped onto the three constructs of dynamic capability theory via selective coding. Fig. 1 illustrates the coding logic by showing how first-order interview evidence is aggregated into subcategories and then linked to the seizing capability dimension. This structured mapping explains how AI empowers creative organizations.

To minimize subjective bias, two independent coders analyzed a random 20% data subset, achieving a robust 82.4% inter-coder reliability coefficient [5]. Disagreements were resolved via expert triangulation. Finally, theoretical saturation was verified using Company D's independent dataset, confirming that no new concepts emerged.

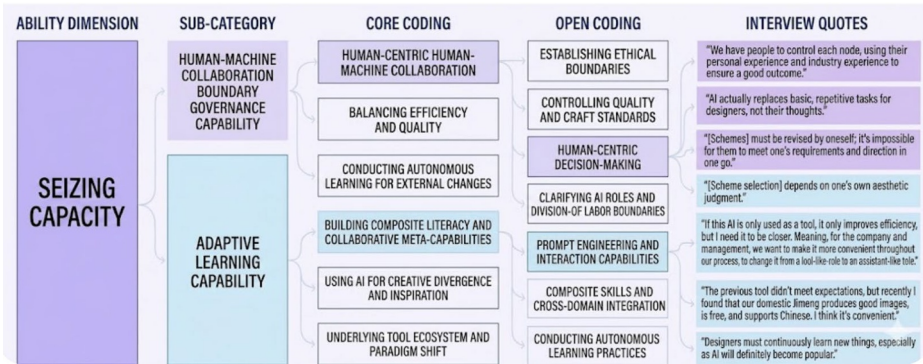


Fig. 1. Coding Process (Using "Seizing Capacity" as an Example)

4 Findings

4.1 Micro-mechanisms of AI Practices in Design SMEs

Based on a systematic grounded analysis of multi-case data, this study reveals that the AI-driven digital upgrading of design-intensive SMEs does not manifest as a static accumulation of technological resources, but rather as specific operational mechanisms and collaborative pathways of three core capabilities—sensing, seizing, and transforming—across the entire design workflow [13]. Table 1 presents the core coding structure and the specific action mechanisms of these capabilities.

Table 1. Core Coding Structure of Dynamic Capabilities

Core Code	Subcategory	Axial Coding
Sensing Capability	Technology Sensing	Assessing AI capabilities
	User Sensing	Using AI for market insights
Seizing Capability	Human-AI Collaboration	Human-centered collaboration
	Adaptive Learning	Balancing efficiency and quality
		Systematic self-learning
		Building composite literacy
Transforming Capability	Process & Organizational Restructuring	Leveraging AI for creative divergence
		Workflow restructuring
	Digital Asset Codification	Evolution of team collaboration
		Digitizing design knowledge
	Change Management	Copyright risk awareness
		Coping with transformation pains

Sensing capability. By identifying and interpreting opportunities, organizations demonstrate the synergy of technological sensing and user sensing in the AI context.

Technological sensing requires individuals to critically assess the capability boundaries of AI, such as Company A's recognition of AI's limitations in complex craftsmanship, which effectively avoids blind technological investments. On this basis, user sensing leverages AI's powerful data processing capabilities for front-end insights, generates massive reference images to anchor preferences, rapidly explores visual styles, and accelerates the efficiency of Front-End process.

Seizing capability. Seizing capability requires the organization to rapidly reshape its working mode after sensing opportunities to capture value, which is fundamentally manifested as adaptive learning and human-machine collaboration boundary governance. The former drives individuals to quickly break through tool barriers; the latter ensures human agency by clarifying the human-machine division of labor. Taking Company A as an example, it introduces a cross-disciplinary network to conduct secondary filtering of AI sketches from realistic constraint dimensions such as structure and cost, bridging the gap between generated outputs and implementation standards, thereby achieving a dynamic balance between efficiency and quality.

Transforming capability. Transforming capability encompasses process reengineering, digital asset codification, and transformation resilience. It begins by systematically reconfiguring the core business architecture rather than simply embedding new technologies. The efficient operation of the new pipeline relies on experience parameterization and tool encapsulation to achieve the systematic precipitation and continuous iteration of core knowledge. Through the establishment of explicit prompt libraries and craft knowledge bases, supplemented by cross-functional knowledge sharing mechanisms, organizations promote the transformation of local explorations into organizational standards, ensuring the institutionalized rooting of the new workflow. This mechanism drives the organization to a fundamental paradigm shift from "relying on individual tacit experience" to "relying on shared digital assets". This allows them to maintain the continuity of core knowledge assets under the impact of generative AI, and further build a long-term competitive advantage that adapts to the human-machine symbiosis paradigm and is difficult to replicate.

5 Conclusion

Based on the perspective of dynamic capability theory, this study identifies the three-dimensional micro-mechanisms and convergence paths through which design-intensive SMEs develop AI-enabled sensing, seizing, and transforming capabilities. More importantly, the proposed "identifying-reshaping-solidifying" process helps open the "black box" of dynamic capabilities in the AI context highlighted by Felin et al. [4]. It specifies how individual and team-level practices, including evaluating AI capability boundaries, externalizing design intent into structured inputs, screening generated results, and codifying project experience, are translated into firm-level capability renewal. In this sense, the study extends dynamic capability theory from a macro-level account of strategic adaptation to the micro-practices of creative SMEs, whose competitive advantages depend heavily on tacit aesthetic judgment, user insight, craft knowledge, and project experience.

The managerial implication is that capability evolution should ultimately serve the redesign of the design process and the generation of product innovation, rather than remaining a change in organizational management form. Managers can operationalize the framework by building a new AI-enabled product development pipeline. This requires constructing standardized prompt libraries around recurrent design tasks, customer scenarios, brand styles, material constraints, and review criteria [18]; clarifying human-AI collaboration boundaries so that AI supports inspiration expansion, variant generation, information organization, and early visualization, while designers retain responsibility for problem framing, aesthetic judgment, feasibility evaluation, and final decision-making; and linking generated outputs, review comments, manufacturing constraints, and delivery files to reusable digital assets. In practice, the prompt library should not be treated as a collection of isolated commands, but as a modular knowledge infrastructure that records task context, input variables, reference images, negative prompts, evaluation rubrics, and reusable constraints. By embedding this infrastructure into briefing, concept generation, scheme review, and delivery archiving, managers can turn individual trial-and-error into a shared R&D routine. Through this pipeline, AI use can be transformed from fragmented experimentation into a repeatable product R&D process that improves concept iteration, cross-role coordination, and product innovation continuity.

This study also has limitations. The empirical evidence is drawn from a multiple-case study of three design-intensive SMEs in South China, which supports mechanism exploration but limits the breadth and generalizability of the findings. Future research can verify the proposed mechanism through large-sample quantitative studies, especially by testing the relationships among AI-enabled sensing, seizing, transforming, knowledge externalization, workflow redesign, and product innovation performance. Longitudinal research is also needed to trace how rapid technological iteration, multimodal AI tools, proprietary data governance, and changing human-AI boundaries shape the long-term capability evolution of design-intensive SMEs.

References

1. Lanfranchi, G., Cioli, A., Amanti, A., et al.: Reconfiguring competitive advantage: a resource dynamic framework for generative AI adoption in digital content marketing. *European Journal of Innovation Management* 29(3), 770-798 (2026). <https://doi.org/10.1108/EJIM-03-2024-0317>.
2. Feuerriegel, S., Hartmann, J., Janiesch, C., Zschech, P.: Generative AI. *Business & Information Systems Engineering* 66, 111-126 (2024). <https://doi.org/10.1007/s12599-023-00834-7>.
3. Teece, D.J.: Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28(13), 1319-1350 (2007). <https://doi.org/10.1002/smj.640>.
4. Felin, T., Foss, N.J., Ployhart, R.E.: Microfoundations of dynamic capabilities. In: Teece, D.J., Leih, S. (eds.) *The Oxford Handbook of Dynamic Capabilities*, pp. 45-72. Oxford University Press, Oxford (2023). <https://doi.org/10.1093/oxfordhb/9780192895452.013.3>

5. Miles, M.B., Huberman, A.M.: *Qualitative data analysis: An expanded sourcebook*. 2nd edn. Sage, Thousand Oaks (1994).
<https://us.sagepub.com/en-us/nam/qualitative-data-analysis/book246128>.
6. Fu, Y., Song, G., Yao, Y., et al.: Creativity in the age of AI: evaluating the impact of generative AI on design outputs and designers' creative thinking. *arXiv* (2024).
<https://arxiv.org/abs/2411.00168>.
7. Oktaý, J.S.: *Grounded Theory*. Oxford University Press, New York (2012).
<https://doi.org/10.1093/acprof:oso/9780199753697.001.0001>.
8. Sirmon, D.G., Hitt, M.A., Ireland, R.D., Gilbert, B.A.: Resource orchestration to create competitive advantage. *Journal of Management* 37(5), 1390-1412 (2011).
<https://doi.org/10.1177/0149206310385695>.
9. Mikalef, P., Gupta, M.: Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management* 58(3), 103434 (2021).
<https://doi.org/10.1016/j.im.2021.103434>.
10. Teece, D.J., Pisano, G., Shuen, A.: Dynamic capabilities and strategic management. *Strategic Management Journal* 18(7), 509-533 (1997).
[https://doi.org/10.1002/\(SICI\)1097-0266\(199708\)18:7<509:AID-SMJ882>3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509:AID-SMJ882>3.0.CO;2-Z).
11. Feldman, M.S., Pentland, B.T.: Reconceptualizing organizational routines as a source of flexibility and change. *Administrative Science Quarterly* 48(1), 94-118 (2003).
<https://doi.org/10.2307/3556620>.
12. Vial, G.: Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems* 28(2), 118-144 (2019).
<https://doi.org/10.1016/j.jsis.2019.01.003>.
13. Warner, K.S., Wäger, M.: Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning* 52(3), 326-349 (2019).
<https://doi.org/10.1016/j.lrp.2018.12.001>.
14. Yin, R.K.: *Case Study Research and Applications*. 6th edn. SAGE, Los Angeles (2018).
<https://us.sagepub.com/en-us/nam/case-study-research-and-applications/book250150>.
15. Epstein, Z., Hertzmann, A., Herman, L., et al.: Art and the science of generative AI. *Science* 380(6650), 1110-1111 (2023). <https://doi.org/10.1126/science.adh4451>.
16. Dell'Acqua, F., McFowland, E., Mollick, E.R., et al.: Navigating the jagged technological frontier: field experimental evidence of the effects of AI on knowledge worker productivity and quality. *Harvard Business School Working Paper* 24-013 (2023).
<https://www.hbs.edu/faculty/Pages/item.aspx?num=64700>.
17. Jiang, J., Wu, Y., Zhang, Y., et al.: HAIGEN: towards human-AI collaboration for facilitating creativity and style generation in fashion design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8(3), Article 102 (2024).
<https://doi.org/10.1145/3678518>.
18. White, J., Fu, Q., Hays, S., et al.: A prompt pattern catalog to enhance prompt engineering with ChatGPT. *arXiv* (2023). <https://arxiv.org/abs/2302.11382>.

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