Proceedings of ICMRED 2026 Symposium: Financial Innovation, Risk Governance, and the Dynamics of Global Capital Flows
DOI: 10.54254/2754-1169/2026.BL34568

Generative AI, Digital Infrastructure, and Firm Productivity: A Task-to-Firm Conversion Framework for Chinese Firms

Jinliang Mai

Faculty of Business and Economics, University of Melbourne, Melbourne, Australia
maijinliang857@gmail.com

Abstract. This paper reviews current published research on how generative artificial intelligence affects firm productivity. Rather than conducting new firm-level data analysis, it synthesizes evidence from artificial intelligence research, task-level productivity experiments, general-purpose technology theory, digital economics, and China-focused digital transformation studies. The central question is why GenAI produces measurable productivity gains in some work settings but uneven or limited firm-level effects in others. The review develops a task-to-firm conversion framework, arguing that GenAI should not be treated as a standalone productivity shock. Its economic value depends on the interaction between model capability, task fit, human-AI calibration, organizational complementary assets, and regional digital infrastructure. Existing studies show that GenAI can improve writing, customer support, consulting, and software-development tasks, but they also reveal risks of overreliance, misalignment, and uneven performance. For Chinese firms, the review suggests that productivity gains are most likely when GenAI adoption is supported by cloud infrastructure, data readiness, skilled labor, workflow redesign, and strong digital ecosystems.

Keywords: Generative AI, firm productivity, digital infrastructure, general-purpose technology, literature review

1. Introduction

Generative artificial intelligence has rapidly moved from a technical innovation to a widely used business technology. Its recent development is built on transformer architectures and large language models, which allow systems to generate, summarize, translate, classify, and recombine language-based information across many work contexts [1, 2]. Because these models can be adapted to writing, coding, customer service, research, decision support, and managerial communication, scholars increasingly describe GenAI as a foundation-model technology with broad economic implications [3, 4].

At the same time, the productivity effects of GenAI remain unsettled. Task-level studies show that GenAI can raise output speed and quality in writing, customer support, consulting, and software-development tasks [5-8]. However, these gains do not automatically become firm-level productivity improvements. Like earlier general-purpose technologies, GenAI requires complementary investment, organizational redesign, worker learning, and institutional support before its benefits can diffuse widely [9, 10]. Digital infrastructure also matters because cloud services, broadband access, platform ecosystems, and data resources shape whether firms can use advanced digital tools effectively [11, 12].

The research gap is not simply whether GenAI is productive but how task-level productivity gains are converted into firm-level productivity. Existing studies are fragmented across AI capability research, task-level experiments, macroeconomic assessments, digital-economy theory, and China-focused firm studies [13-16]. This paper addresses that gap through an integrative literature review. It asks how current published research explains the conditions under which GenAI adoption improves firm productivity, and why digital infrastructure and organizational capability shape whether task-level gains become firm-level productivity improvements. The paper contributes a task-to-firm conversion framework: model capability and task fit create potential gains, but firm-level productivity depends on human-AI calibration, organizational assets, and regional digital infrastructure.

2. Conceptual and theoretical background

2.1. Generative AI as a foundation-model technology

The first conceptual foundation is that GenAI differs from many earlier digital tools because it operates as a flexible foundation-model technology. The transformer architecture made it possible to model long-range relationships in language and other sequential data, while large language models showed that scale can produce general capabilities such as few-shot learning, instruction following, summarization, and code generation [1, 2]. Foundation models are not built for a single fixed task. They provide adaptable capabilities that downstream users can apply to many domains, including marketing, finance, legal drafting, software development, product design, and internal knowledge management [3]. This flexibility explains why firms are interested in GenAI as a productivity technology rather than merely as a communication tool.

2.2. Generative AI as a general-purpose technology

A second foundation is general-purpose technology theory. Bresnahan and Trajtenberg argue that a general-purpose technology has broad application, technological dynamism, and strong complementarities with other forms of innovation [9]. GenAI fits this logic because its usefulness expands across tasks and improves as models, interfaces, data pipelines, and organizational routines develop. Yet general-purpose technologies often show delayed productivity effects. Brynjolfsson, Hitt, and Yang show that information technology becomes valuable when combined with intangible organizational capital, not when purchased in isolation [10]. This insight is central to GenAI. Firms may adopt chatbots or coding assistants quickly, but productivity gains require redesigning workflows, changing responsibilities, building data access, and training workers to use model outputs critically.

2.3. Digital economics and infrastructure

Digital economics further clarifies why GenAI can affect productivity. Digital technologies often reduce search, replication, transportation, tracking, and verification costs [11]. GenAI extends this logic into knowledge work by lowering the cost of drafting, classifying, summarizing, translating, and recombining information. However, such gains depend on infrastructure. Broadband evidence

DOI: 10.54254/2754-1169/2026.BL34568

shows that digital connectivity can complement skilled labor and raise productivity only when workers and firms can reorganize around the new technology [12]. For GenAI, regional digital infrastructure includes broadband, cloud computing, data centers, digital platforms, technical talent, cybersecurity systems, and local innovation ecosystems. These conditions matter because GenAI is computationally intensive and often requires reliable access to data, cloud services, and complementary digital tools.

2.4. China-focused context

China is a useful but methodologically difficult context for this review. Its firms operate within highly uneven digital ecosystems, so regional infrastructure may shape whether GenAI adoption becomes productive. Studies of regional digital economy development in China suggest that digital infrastructure can improve enterprise productivity, but the gains vary across regions and depend on local economic conditions [13]. Firm-level digital transformation evidence also indicates that digital adoption can improve performance when it is connected to broader organizational change rather than superficial digital labeling [14]. Recent China-focused AI evidence is promising, but it remains early and cannot yet settle the long-run productivity effects of GenAI [15]. The China section of this paper transfers mechanisms cautiously rather than claiming direct causal proof.

3. Analytical framework and propositions

3.1. Model capability and task fit

The first proposition is that GenAI is more likely to improve productivity when the model capability fits the task. GenAI performs best when work depends on language, coding, summarization, information retrieval, classification, or recombination of existing knowledge. Noy and Zhang find that access to ChatGPT improved both speed and quality in professional writing tasks, especially for participants who initially performed below the median [5]. Brynjolfsson, Li, and Raymond find that a generative AI assistant improved customer-support productivity, with particularly large benefits for less experienced workers [6]. These studies support the task-level part of the framework: GenAI can reduce the cost of producing acceptable first drafts, retrieving procedural knowledge, and standardizing responses.

The limitation is that task fit also explains why productivity gains are not universal. GenAI is less reliable when tasks require precise factual grounding, high-stakes judgment, tacit contextual knowledge, or accountability for errors. The same model that accelerates drafting may produce false citations, misleading summaries, or confident but incorrect recommendations. Thus, model capability is only the first conversion condition. A task must also have verifiable outputs and a workflow in which workers can evaluate model suggestions.

3.2. Human-AI calibration and the jagged frontier

The second proposition is that human-AI calibration determines whether task-level gains persist. Dell'Acqua and colleagues describe a jagged technological frontier: AI improves performance on some tasks while harming performance on tasks that appear similar but lie outside the model's effective capability range [7]. This finding is important because it prevents a simplistic view of GenAI as uniformly beneficial. Workers may gain speed inside the frontier, but outside it, they may overtrust outputs, underinvest in independent reasoning, or fail to detect errors.

DOI: 10.54254/2754-1169/2026.BL34568

Cui and colleagues' field experiments with software developers add another caution. GenAI tools can improve some aspects of high-skilled work, but effects vary across contexts, tasks, and evaluation measures [8]. This evidence complicates the positive findings from writing and customer-support studies. It suggests that productivity depends on whether workers can judge where GenAI is helpful, where it is misleading, and when expert verification is necessary. For firms, training cannot focus only on tool access. Productivity gains require workers to calibrate trust, managers to define appropriate use cases, and organizations to build review routines.

3.3. Organizational complementary assets

The third proposition is that firms convert task-level gains into firm-level productivity only when GenAI is combined with complementary assets. A worker may write faster with GenAI, but the firm gains productivity only if the surrounding workflow also changes. If review, approval, compliance, data access, and coordination processes remain slow, local acceleration may produce little aggregate gain. The general-purpose technology literature predicts this pattern because complementary innovation is often more important than initial adoption [9, 10].

Key complements include clean internal data, cloud systems, cybersecurity, employee training, process redesign, and managerial governance. Data readiness matters because GenAI becomes more valuable when it can interact with firm-specific knowledge rather than generic public information. Workflow redesign matters because productivity depends on reallocating tasks between humans and machines. Governance matters because uncontrolled use may create legal, privacy, quality, or reputational risks. Thus, the central firm-level question is not whether GenAI is present but whether it is embedded in a productive organizational system.

3.4. Regional digital infrastructure

The fourth proposition is that regional digital infrastructure strengthens the productivity value of GenAI. Firms in digitally advanced regions are more likely to access cloud providers, digital platforms, skilled labor, data services, and peer learning networks. These external conditions reduce the cost of experimentation and make complementary innovation easier. Evidence from China's regional digital economy supports the view that infrastructure and productivity are linked, especially when digital services become part of firms' broader production systems [13]. Digital transformation studies in China also imply that firms with stronger internal digital capability are better positioned to benefit from advanced AI tools [14]. GenAI diffusion may therefore intensify regional productivity differences if digitally developed regions adopt faster and learn more effectively.

4. Review scope and source selection

This paper uses an integrative literature-review approach because GenAI productivity research is still new and scattered across several fields. The review gives priority to peer-reviewed journal articles and authoritative working papers from computer science, economics, management, information systems, and China-focused digital economy research. The time scope begins in 2017 with the transformer architecture and extends through recent published and forthcoming work on GenAI productivity. Foundational theory papers published before 2017 are included when they explain general-purpose technologies, organizational capital, or digital infrastructure.

Sources are included when they directly address GenAI, AI productivity, digital infrastructure, firm productivity, or literature-review guidance; when they come from respected academic venues or

DOI: 10.54254/2754-1169/2026.BL34568

working-paper series; and when they offer mechanisms, evidence, or concepts relevant to the research question. Sources are excluded when they are blogs, unsourced summaries, unverifiable PDFs, or practitioner commentary used as academic evidence. This exclusion matters because the public debate around GenAI is rich in predictions but thinner in verified evidence. Practitioner reports may help motivate business relevance, but the argument of this paper relies on academic studies and credible institutional evidence.

The synthesis follows an integrative and concept-centric logic recommended for literature reviews [17, 18]. Instead of listing studies one by one, the paper organizes them around five themes: technology foundations, task-level productivity evidence, organizational complementarity, regional digital infrastructure, and China-specific implications. This structure is appropriate because the question is analytical rather than statistical. The goal is to explain why published findings differ and to develop a framework for future empirical work, not to estimate a new causal coefficient.

5. Thematic synthesis and discussion

5.1. Task-level gains are meaningful but bounded

The strongest evidence for GenAI productivity currently comes from task-level and occupation-specific studies. Writing experiments show that GenAI can reduce completion time and improve output quality for many users [5]. Customer-support evidence shows that AI assistance can raise productivity by helping workers respond faster and learn from better examples [6]. Consulting and software-development studies similarly show that GenAI can support complex knowledge work, but only for tasks that fit the tool's strengths [7, 8]. Taken together, this evidence supports a cautious positive conclusion: GenAI can improve productivity, but the effect is bounded by task characteristics and evaluation standards.

5.2. Productivity effects are uneven across workers and tasks

A repeated pattern is heterogeneity. Less experienced or lower-performing workers often gain more because GenAI supplies templates, language, examples, and procedural guidance that narrow skill gaps [5, 6]. However, high-skilled workers may benefit differently. They may use GenAI to accelerate routine parts of complex work, but they also face greater risks when model suggestions conflict with expert judgment. This heterogeneity matters for firms because average productivity effects can hide important distributional changes. GenAI may democratize some capabilities while also increasing the value of workers who know how to supervise, verify, and integrate AI outputs.

5.3. The jagged frontier creates performance risk

The jagged frontier is one of the most useful concepts in current GenAI research because it explains why the same technology can improve and reduce performance [7]. Inside the frontier, GenAI can generate useful drafts, code suggestions, summaries, and response templates. Outside the frontier, it can produce plausible but flawed outputs that slow work or degrade quality. The risk is especially serious when users cannot see the boundary. A firm that adopts GenAI without clear use cases, verification standards, or accountability routines may mistake fluency for reliability. This risk supports Acemoglu's caution that AI's macroeconomic productivity effects may be smaller than popular narratives suggest if adoption focuses on easy automation rather than genuinely valuable task transformation [16].

DOI: 10.54254/2754-1169/2026.BL34568

5.4. Complementary assets link adoption to firm productivity

The most important implication of the literature is that adoption is not the same as productivity. GenAI can be present in a firm without changing firm-level output per unit of input. Productivity requires complementary assets that allow local task gains to reshape the production system. Organizational capital is central because firms must redesign processes, update incentives, define responsibility for AI outputs, and build feedback loops [10]. Digital economics also suggests that value emerges when information-cost reductions are connected to broader coordination and decision systems [11].

For example, a marketing department may draft campaigns faster with GenAI, but productivity rises only if approval processes, customer data access, brand controls, and performance measurement are redesigned. A software team may generate code more quickly, but firm-level gains depend on testing, security review, documentation, and integration. These examples show why many firms may observe visible adoption but limited productivity improvement. The bottleneck moves from content generation to system integration.

5.5. Regional infrastructure shapes diffusion and conversion

Regional digital infrastructure is especially relevant for Chinese firms, but the evidence must be interpreted cautiously. Digital infrastructure affects access to cloud computing, model services, broadband, data resources, and technical workers. It also creates local spillovers because firms learn from suppliers, platforms, universities, and peer organizations in the same ecosystem. Evidence from the Yangtze River Delta suggests that regional digital economy development can support enterprise productivity [13]. Firm-level digital transformation evidence from China similarly indicates that performance gains depend on substantive digital capability rather than symbolic adoption [14].

This implies, but does not yet prove, that GenAI may widen regional differences if firms in stronger digital regions adopt faster, integrate better, and accumulate learning advantages. At the same time, policy can reduce this risk by expanding cloud access, digital skills training, data governance standards, and infrastructure investment in less developed regions. For managers, the lesson is that GenAI strategy should not begin with model choice alone. It should begin with an assessment of data readiness, workflow bottlenecks, worker skills, and infrastructure constraints.

5.6. Implications for Chinese firms and policymakers

For Chinese firms, the practical implication is to treat GenAI as part of a broader digital production system. Firms should identify tasks where output can be evaluated, build controlled pilot projects, train employees in verification, and connect GenAI tools to internal knowledge bases only with appropriate data governance. They should also measure productivity at the workflow level rather than counting adoption events or keyword disclosures. For policymakers, the review suggests that GenAI productivity depends on complementary public goods: broadband, cloud infrastructure, digital standards, AI talent, and support for small and medium-sized firms. The goal should be not only faster AI adoption but also higher-quality adoption that helps firms convert task-level improvements into durable productivity gains.

DOI: 10.54254/2754-1169/2026.BL34568

6. Conclusion

This paper reviewed current published research on GenAI, digital infrastructure, and firm productivity. The central conclusion is that GenAI can improve productivity, but it should not be understood as a standalone productivity shock. Its value depends on a chain of complements. Model capability and task fit create the possibility of productivity improvement; human-AI calibration determines whether workers use the technology wisely; organizational assets determine whether local gains scale across workflows; and regional digital infrastructure shapes whether firms can access and integrate the necessary digital resources.

The review also shows why current evidence appears mixed. Task-level studies provide credible evidence of gains in writing, customer support, consulting, and software development, but these gains are bounded by the jagged frontier and by the need for verification [5-8]. General-purpose technology theory explains why firm-level effects may emerge slowly, because complementary investment and organizational redesign take time [9, 10]. China-focused studies suggest that digital infrastructure and digital transformation are relevant productivity conditions, but GenAI-specific firm evidence remains limited [13-15].

Future research should therefore measure GenAI adoption more carefully, distinguish symbolic adoption from substantive workflow integration, and use longitudinal firm-level evidence to identify causal effects. China-focused research should examine regional differences, industry heterogeneity, and the interaction between GenAI tools, cloud infrastructure, data governance, and worker capability. The main limitation of this paper is that it synthesizes published work rather than estimating new empirical effects. Nevertheless, the review provides a clearer argument than adoption-centered accounts: GenAI productivity depends less on adoption alone than on the digital and organizational systems that convert adoption into productive capability.

References

[1] Vaswani A., Shazeer N., Parmar N., et al. (2017) Attention is all you need. Advances in Neural Information Processing Systems. https: //papers.nips.cc/paper/7181-attention-is-all-you-need
[2] Brown T.B., Mann B., Ryder N., et al. (2020) Language models are few-shot learners. Advances in Neural Information Processing Systems, 33: 1877-1901.
[3] Bommasani R., Hudson D.A., Adeli E., et al. (2021) On the opportunities and risks of foundation models. doi: 10.48550/arXiv.2108.07258.
[4] Eloundou T., Manning S., Mishkin P., Rock D. (2024) GPTs are GPTs: labor market impact potential of LLMs. Science, 384(6702): 1306-1308. doi: 10.1126/science.adj0998.
[5] Noy S., Zhang W. (2023) Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654): 187-192. doi: 10.1126/science.adh2586.
[6] Brynjolfsson E., Li D., Raymond L.R. (2025) Generative AI at work. Quarterly Journal of Economics, 140(2): 889-942. doi: 10.1093/qje/qjae044.
[7] Dell'Acqua F., McFowland E., Mollick E.R., et al. (2026) Navigating the jagged technological frontier: field experimental evidence of the effects of artificial intelligence on knowledge worker productivity and quality. Organization Science, 37(2): 403-423. doi: 10.1287/orsc.2025.21838.
[8] Cui K.Z., Demirer M., Jaffe S., Musolff L., Peng S., Salz T. (2026) The effects of generative AI on high-skilled work: evidence from three field experiments with software developers. Management Science. doi: 10.1287/mnsc.2025.00535.
[9] Bresnahan T.F., Trajtenberg M. (1995) General purpose technologies: engines of growth? Journal of Econometrics, 65(1): 83-108. doi: 10.1016/0304-4076(94)01598-T.
[10] Brynjolfsson E., Hitt L.M., Yang S. (2002) Intangible assets: computers and organizational capital. Brookings Papers on Economic Activity, (1): 137-198.
[11] Goldfarb A., Tucker C. (2019) Digital economics. Journal of Economic Literature, 57(1): 3-43. doi: 10.1257/jel.20171452.

DOI: 10.54254/2754-1169/2026.BL34568

[12] Akerman A., Gaarder I., Mogstad M. (2015) The skill complementarity of broadband internet. Quarterly Journal of Economics, 130(4): 1781-1824. doi: 10.1093/qje/qjv028.
[13] Huang J., Shen Y., Chen J., Zhou Y. (2022) Regional digital economy development and enterprise productivity: a study of the Chinese Yangtze River Delta. Regional Science Policy & Practice, 14(S2): 118-137. doi: 10.1111/rsp3.12559.
[14] Zhai H., Yang M., Chan K.C. (2022) Does digital transformation enhance a firm's performance? Evidence from China. Technology in Society, 68: 101841. doi: 10.1016/j.techsoc.2021.101841.
[15] Sun Q., Huang M. (2026) Firm-level evidence on AI-driven output expansion and productivity in China. Socio-Economic Planning Sciences, 103: 102389. doi: 10.1016/j.seps.2025.102389.
[16] Acemoglu D. (2025) The simple macroeconomics of AI. Economic Policy, 40(121): 13-58. doi: 10.1093/epolic/eiae042.
[17] Snyder H. (2019) Literature review as a research methodology: an overview and guidelines. Journal of Business Research, 104: 333-339. doi: 10.1016/j.jbusres.2019.07.039.
[18] Webster J., Watson R.T. (2002) Analyzing the past to prepare for the future: writing a literature review. MIS Quarterly, 26(2): xiii-xxiii.