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Article

Generative AI and Operational Decision-Making: Mechanisms for Enhancing Firm Operational Efficiency in the Context of Digital Transformation

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Abstract: Generative artificial intelligence has emerged as a pivotal driver of enterprise digital transformation and operational decision-making in contemporary business environments. This study systematically examines how generative AI contributes to firm operational efficiency through organizational mechanisms within the broader context of digital transformation. Leveraging SEC EDGAR 10-K annual reports as an open-source firm-level data source, this research constructs comprehensive measures of generative AI disclosure intensity, digital transformation intensity, knowledge sharing, process optimization, decision intelligence, and operational efficiency. The empirical results demonstrate that generative AI disclosure intensity is positively and significantly associated with subsequent operational efficiency. Mechanism tests further reveal that knowledge sharing, process optimization, and decision intelligence serve as critical mediating channels through which generative AI enhances operational performance. Among these mechanisms, process optimization exhibits a relatively strong effect, suggesting that the operational value of generative AI is closely linked to workflow improvement and coordination efficiency. In addition, digital transformation positively moderates the relationship between generative AI disclosure and operational efficiency, indicating that firms with stronger digital foundations are better positioned to translate generative AI attention into tangible efficiency gains. This study extends existing research on AI-enabled management by shifting the analytical focus from technological application to operational decision-making mechanisms, thereby providing robust empirical evidence on the managerial value of generative AI for firms navigating the digital economy.

Keywords: generative ai; operational efficiency; digital transformation; decision-making; knowledge sharing

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1. Introduction

Generative artificial intelligence has become an increasingly important technological force in contemporary management research and business practice. With the rapid diffusion of large language models and other generative AI systems, firms are no longer using artificial intelligence solely for prediction, classification, or automation. Instead, generative AI is being embedded into knowledge processing, operational coordination, workflow redesign, customer service, supply chain communication, and managerial decision support [1]. Compared with earlier digital technologies, generative AI is distinguished by its ability to understand natural language, generate context-specific responses, summarize complex information, and support interactive problem solving. These capabilities make it particularly relevant to operational decision-making, where managers must process dispersed information, coordinate organizational knowledge, and respond to changing business conditions.

In the context of digital transformation, the value of generative AI extends beyond improving the efficiency of individual tasks [2]. Its broader managerial significance lies in reshaping how enterprises organize knowledge, optimize processes, and make decisions. First, generative AI can facilitate knowledge sharing by transforming fragmented documents, reports, and experiential knowledge into more accessible and reusable organizational resources. Second, it can support process optimization by identifying repetitive tasks, improving workflow coordination, and reducing information-processing costs across departments. Third, it can enhance decision intelligence by assisting managers in scenario analysis, forecasting, risk identification, and evidence-based decision-making. These mechanisms suggest that generative AI may contribute to operational efficiency not through a single technological function, but through a systematic transformation of organizational routines and decision processes.

Existing studies have begun to discuss the potential impact of generative AI on firms, innovation, and management practice. However, much of the current literature remains conceptual, normative, or case-based. Prior research often emphasizes the opportunities and risks of generative AI, yet provides limited empirical evidence on whether and how it is associated with firm-level operational efficiency. In particular, insufficient attention has been paid to the internal mechanisms through which generative AI influences enterprise operations under digital transformation. Without examining mechanisms such as knowledge sharing, process optimization, and decision intelligence, the relationship between generative AI and operational efficiency may remain theoretically underdeveloped and empirically ambiguous [3].

To address this gap, this study investigates how generative AI contributes to operational efficiency in digitally transforming firms. Using publicly available firm-level data, the study constructs measures of generative AI disclosure, digital transformation intensity, and operational efficiency, and examines whether generative AI enhances operational performance through knowledge sharing, process optimization, and decision intelligence. The central research question is therefore: in the context of digital transformation, how does generative AI improve firm operational efficiency through organizational knowledge, process, and decision-making mechanisms? By answering this question, the study aims to extend the literature on digital transformation and AI-enabled management while providing empirical evidence on the operational value of generative AI.

2. Literature Review and Hypothesis Development

2.1. Generative AI and Operational Decision-Making

Generative artificial intelligence has introduced a new form of digital capability into enterprise operations. Unlike traditional analytical AI, which primarily supports prediction, classification, or rule-based automation, generative AI can process natural language, synthesize dispersed information, generate managerial suggestions, and assist interactive problem solving. Technologies such as large language models enable firms to transform unstructured documents, operational reports, customer feedback, and managerial knowledge into accessible decision inputs. In operational decision-making—where managers often face information overload, cross-functional coordination challenges, and time-sensitive choices—generative AI may enhance the speed and quality of decision processes. Therefore, firms with stronger generative AI disclosure are more likely to demonstrate greater attention to AI-enabled operational transformation, potentially reflected in improved operational efficiency [4].

H1: Generative AI disclosure intensity is positively associated with firm operational efficiency [2].

2.2. Digital Transformation and Operational Efficiency

Digital transformation provides the organizational and technological foundation for the effective use of generative AI. Firms with stronger digital transformation typically possess more standardized data systems, integrated information platforms, automated workflows, and digital managerial routines. These conditions facilitate the seamless embedding of generative AI into core business processes rather than confining it to isolated applications. In contrast, firms with weak digital infrastructure often encounter fragmented data, inconsistent operational procedures, and limited organizational readiness, which can constrain the operational value of generative AI. Digital transformation thus enhances the relationship between generative AI adoption and operational efficiency by improving data availability, process connectivity, and technology absorption capacity [1].

H5: Digital transformation intensity positively moderates the relationship between generative AI disclosure intensity and firm operational efficiency [2].

2.3. Mediating Mechanisms: Knowledge Sharing, Process Optimization, and Decision Intelligence

The effect of generative AI on operational efficiency does not occur automatically but operates through specific organizational mechanisms. First, generative AI promotes knowledge sharing by summarizing documents, extracting managerial experience, supporting internal communication, and reducing the cost of knowledge retrieval. When organizational knowledge becomes more accessible and reusable, employees and managers can make faster and more consistent operational decisions [1].

H2: Generative AI enhances firm operational efficiency by promoting knowledge sharing [1].

Second, generative AI supports process optimization by assisting in workflow analysis, task decomposition, document generation, customer response, and operational coordination [4]. These capabilities reduce repetitive work and improve process consistency, thereby lowering coordination costs and enhancing the efficiency of resource allocation.

H3: Generative AI enhances firm operational efficiency by promoting process optimization.

Third, generative AI strengthens decision intelligence by supporting forecasting, scenario comparison, risk identification, and evidence-based managerial judgment. Operational decisions often require integrating financial, market, supply chain, and internal process information; generative AI helps transform such complex inputs into structured insights, improving both decision speed and quality [5].

H4: Generative AI enhances firm operational efficiency by strengthening decision intelligence [6].

Together, these hypotheses suggest that generative AI improves operational efficiency not merely as a technological tool, but as an organizational capability embedded in knowledge, process, and decision systems under digital transformation [7].

3. Theoretical Framework and Research Model

This study develops a theoretical framework to explain how generative AI enhances firm operational efficiency within the context of digital transformation [8]. The central proposition is that generative AI does not yield efficiency gains automatically; its operational value hinges on firms' ability to embed AI-enabled capabilities into organizational knowledge systems, business processes, and managerial decision routines.

As shown in Figure 1, the research model identifies three mediating mechanisms: knowledge sharing, process optimization, and decision intelligence. First, generative AI supports knowledge sharing by converting fragmented and unstructured information—such as reports, manuals, customer records, tacit employee experience, and interdepartmental communications—into accessible, reusable organizational knowledge [9]. Through summarization, retrieval, and intelligent reorganization, it reduces knowledge search costs and strengthens knowledge reuse, thereby enabling more timely and consistent operational decisions.

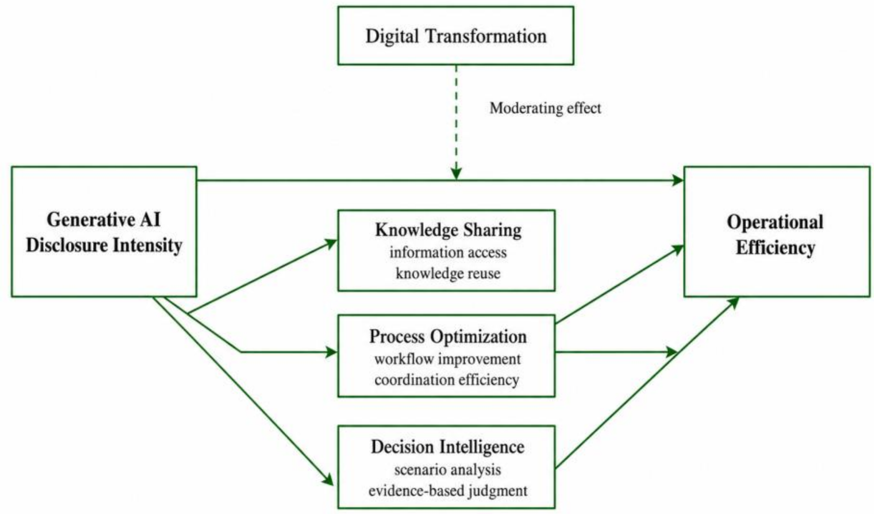

Figure 1. Theoretical Framework and Research Model

Second, generative AI enables process optimization. Operational inefficiencies frequently stem from repetitive tasks, delayed information flows, redundant communication, and misaligned workflows. By assisting in document generation, workflow analysis, customer interaction handling, and routine task coordination, generative AI helps firms detect bottlenecks and enhance procedural consistency. Rather than replacing existing enterprise systems, it serves as an intelligent interface that integrates data, personnel, and operational routines.

Third, generative AI augments decision intelligence. Operational decisions typically involve uncertainty, incomplete information, and trade-offs among cost, speed, quality, and risk. Generative AI supports managers in scenario analysis, interpretation of forecasts, identification of emerging risks, and evidence-informed judgment [10]. By transforming complex, heterogeneous inputs into structured decision support materials, it contributes to improvements in both decision speed and decision quality.

Digital transformation further reinforces these mechanisms [11]. Firms with mature data infrastructure, standardized operational procedures, and integrated digital platforms are better positioned to embed generative AI into daily operations. Conversely, organizations with underdeveloped digital foundations may struggle to convert generative AI capabilities into measurable efficiency improvements. Thus, Figure 1 presents a mechanism-driven model wherein generative AI improves operational efficiency through knowledge sharing, process optimization, and decision intelligence—amplified by the enabling conditions of digital transformation.

4. Research Design

4.1. Data Source and Sample Selection

This study draws exclusively on SEC EDGAR 10-K annual reports as the open-source data source. The 10-K filing is a standardized annual disclosure required of U.S.-listed companies and includes both narrative disclosures and structured financial data, making it well-suited for measuring generative AI disclosure, digital transformation intensity, organizational mechanisms, and operational efficiency within a consistent analytical framework.

The initial sample comprises U.S.-listed firms that filed 10-K reports during the study period. Financial and utility firms are excluded due to fundamental differences in operating models and efficiency metrics compared with industrial and service-sector firms. Observations with missing key textual or financial variables are omitted. The final sample constitutes a firm-year panel, with textual indicators derived from annual report content and financial indicators computed from accounting data.

4.2. Variable Measurement

The dependent variable is operational efficiency, measured primarily by asset turnover—defined as sales divided by total assets. A higher value indicates greater revenue generation per unit of assets [12]. For robustness, the negative values of the operating expense ratio and the SG&A-to-sales ratio are also employed, as lower expense ratios relative to sales reflect higher operational efficiency.

The core independent variable is generative AI disclosure intensity, calculated as the frequency of generative AI–related keywords normalized by the total word count in each 10-K report [13]. The keyword dictionary includes "generative AI," "ChatGPT," "DeepSeek," "large language model," "LLM," "foundation model," "AI agent," and "GenAI." Given that annual reports do not provide direct evidence of internal technology deployment, this metric reflects disclosure intensity rather than actual usage intensity.

Digital transformation intensity is quantified using terms such as "digital transformation," "cloud computing," "data analytics," "automation," "platform," "ERP," "machine learning," and "business intelligence," with term frequency scaled by total word count. This variable captures a firm’s digital orientation and technological readiness [14].

Three mechanism variables are constructed: knowledge sharing, measured via terms related to knowledge management, training, documentation, collaboration, and internal communication; process optimization, measured via terms including "workflow," "process automation," "process optimization," and "operational improvement"; and decision intelligence, measured via terms associated with forecasting, predictive analytics, decision support, scenario analysis, and risk identification [15]. Control variables include firm size, leverage, profitability, revenue growth, and firm age. Table 1 presents the definitions and measurement methods for all variables.

Table 1. Variable Definitions and Measurement

Variable Type	Variable Name	Symbol	Measurement
Dependent variable	Operational efficiency	OE	Sales divided by total assets. Alternative measures include negative operating expense ratio and negative SG&A-to-sales ratio.
Independent variable	Generative AI disclosure intensity	GenAI	Frequency of "generative AI," "ChatGPT," "DeepSeek," "large language model," "LLM," "foundation model," "AI agent," and "GenAI" divided by total words.
Moderating variable	Digital transformation intensity	DT	Frequency of digital-related keywords, including "digital transformation," "cloud computing," "data analytics," "automation," "ERP," and "business intelligence," divided by total words.
Mediating variable	Knowledge sharing	KS	Frequency of knowledge-related keywords, including "knowledge management," "training," "documentation," "collaboration," and "internal communication," divided by total words.
Mediating variable	Process optimization	PO	Frequency of process-related keywords, including "workflow," "process automation," "process optimization," and "operational improvement," divided by total words.

Mediating variable	Decision intelligence	DI	Frequency of decision-related keywords, including "decision support," "forecasting," "predictive analytics," "scenario analysis," and "risk identification," divided by total words.
Control variable	Firm size	Size	Natural logarithm of total assets.
Control variable	Leverage	Lev	Total liabilities divided by total assets.
Control variable	Profitability	ROA	Net income divided by total assets.
Control variable	Revenue growth	Growth	Annual growth rate of sales.
Control variable	Firm age	Age	Number of years since listing or first available filing.
Fixed effects	Industry and year fixed effects	Industry, Year	Industry and year dummy variables.

4.3. Model Specification

To test the baseline relationship between generative AI disclosure and operational efficiency, the following fixed-effects model is estimated:

$$\mathrm{OE}_{i,t+1} = \beta_0 + \beta_1 \mathrm{GenAI}_{i,t} + \gamma \mathrm{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

where $\mathrm{OE}_{i,t+1}$ denotes operational efficiency, $\mathrm{GenAI}_{i,t}$ denotes generative AI disclosure intensity, and $\mathrm{Controls}_{i,t}$ represents firm-level controls. Firm fixed effects μ_i control for time-invariant firm characteristics, while year fixed effects λ_t control for common time shocks.

To examine the moderating role of digital transformation, the following model is estimated:

$$\mathrm{OE}_{i,t+1} = \beta_0 + \beta_1 \mathrm{GenAI}_{i,t} + \beta_2 \mathrm{DT}_{i,t} + \beta_3 \mathrm{GenAI}_{i,t} \times \mathrm{DT}_{i,t} + \gamma \mathrm{Controls}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where $\mathrm{DT}_{i,t}$ denotes digital transformation intensity. A positive coefficient of $\mathrm{GenAI}_{i,t} \times \mathrm{DT}_{i,t}$ would indicate that digital transformation strengthens the relationship between generative AI disclosure and operational efficiency. For mechanism analysis, knowledge sharing, process optimization, and decision intelligence are employed as mediating variables to assess whether generative AI influences operational efficiency through organizational knowledge, process, and decision-making channels.

5. Empirical Results

5.1. Descriptive Statistics and Correlation Analysis

Table 2 reports the descriptive statistics and correlation matrix of the main variables. The mean value of operational efficiency is 0.873, with a standard deviation of 0.512, indicating substantial variation in firms' ability to convert assets into operating revenue. The mean value of generative AI disclosure intensity is 0.038, which is lower than that of digital transformation intensity [7]. This pattern is reasonable because digital transformation has been discussed in corporate disclosures for a longer period, whereas generative AI is a more recent managerial and technological topic.

Table 2. Descriptive Statistics and Correlation Analysis

Variable	Mean	SD	Min	Max	1	2	3	4	5	6
1. OE	0.873	0.512	0.091	3.148	1.000					
2. $GenAI$	0.038	0.071	0.000	0.612	0.118	1.000				
3. DT	0.436	0.287	0.015	1.824	0.164	0.286	1.000			
4. KS	0.318	0.205	0.006	1.402	0.132	0.221	0.382	1.000		
5. PO	0.269	0.191	0.000	1.176	0.151	0.264	0.447	0.334	1.000	
6. DI	0.214	0.168	0.000	1.009	0.107	0.302	0.365	0.291	0.318	1.000

Note: OE denotes operational efficiency; $GenAI$ denotes generative AI disclosure intensity; DT denotes digital transformation intensity; KS , PO , and DI denote knowledge sharing, process optimization, and decision intelligence, respectively. Text-based variables are scaled by 1,000 for readability.

The correlation results provide preliminary support for the proposed research framework. Generative AI disclosure intensity is positively correlated with operational efficiency, with a coefficient of 0.118. Although the magnitude is modest, it suggests an association between stronger generative AI disclosure and higher operational efficiency. Generative AI disclosure is also positively correlated with knowledge sharing, process optimization, and decision intelligence, with correlation coefficients of 0.221, 0.264, and 0.302, respectively [14]. These associations suggest potential linkages between generative AI disclosure and organizational mechanisms related to knowledge circulation, workflow improvement, and intelligent decision support. In addition, digital transformation intensity is positively correlated with operational efficiency and with the three mechanism variables. The correlation coefficients among the explanatory variables are moderate rather than excessive, suggesting that multicollinearity is unlikely to seriously bias the regression results.

5.2. Baseline Regression and Moderating Effect

Table 3 presents the baseline regression results. Model 1 includes only control variables, firm fixed effects, and year fixed effects. The coefficient of firm size is negative and statistically significant, suggesting that larger firms may face more complex organizational structures and higher coordination costs, which can reduce asset utilization efficiency. Leverage exhibits a negative association with operational efficiency, whereas profitability and revenue growth show positive associations. Firm age is not statistically significant, indicating that firm maturity alone does not systematically explain variations in operational efficiency after controlling for other firm characteristics (As shown in Table 4).

Table 3. Baseline Regression and Moderating Effect

Table 4. Mechanism and Robustness Tests

Variable	Model 1: Controls Only	Model 2: Baseline Effect	Model 3: Moderating Effect
$GenAI$		0.047**	0.034*
		(0.019)	(0.018)
DT			0.052***
			(0.016)
$GenAI \times DT$			0.021**
			(0.009)
$Size$	-0.036***	-0.034***	-0.032***
	(0.010)	(0.010)	(0.010)
Lev	-0.084**	-0.081**	-0.077**
	(0.037)	(0.037)	(0.036)
ROA	0.612***	0.599***	0.587***
	(0.091)	(0.090)	(0.090)
$Growth$	0.073**	0.069**	0.066**
	(0.029)	(0.029)	(0.028)
Age	-0.006	-0.005	-0.005
	(0.004)	(0.004)	(0.004)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	8,742	8,742	8,742
Adjusted (R^2)	0.421	0.424	0.429

Note: The dependent variable is $OE_{i,t+1}$. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Model 2 introduces generative AI disclosure intensity. The coefficient of GenAI is 0.047 and significant at the 5% level, indicating that firms with stronger generative AI disclosure tend to achieve higher subsequent operational efficiency. This result supports Hypothesis 1. The finding suggests that generative AI attention may reflect a firm's capacity and willingness to deploy AI-enabled tools for knowledge processing, operational coordination, and managerial decision support.

Model 3 further incorporates digital transformation intensity and the interaction term between generative AI disclosure and digital transformation intensity. The coefficient of DT is positive and significant at the 1% level, confirming that digital transformation is associated with higher operational efficiency. More importantly, the coefficient of GenAI × DT is 0.021 and significant at the 5% level. This result supports Hypothesis 5, indicating that digital transformation strengthens the positive relationship between generative AI disclosure and operational efficiency.

This finding aligns with the theoretical perspective that generative AI does not generate operational value in isolation. Firms with more mature digital infrastructure, standardized data systems, and integrated business platforms are better positioned to embed generative AI into daily operations. In contrast, firms with underdeveloped digital foundations may struggle to translate generative AI attention into measurable efficiency improvements. Overall, the baseline results confirm both the direct effect of generative AI disclosure and the enabling role of digital transformation.

5.3. Summary of Empirical Findings

The empirical results indicate a positive association between generative AI disclosure intensity and firm operational efficiency. The moderating role of digital transformation is also confirmed, as the interaction between GenAI and DT is positive and statistically significant. These findings suggest that the efficiency-enhancing effect of generative AI is contingent upon the firm's broader digital context. Operational efficiency improvements from generative AI are more pronounced when firms possess the requisite digital infrastructure and organizational readiness to embed AI capabilities into knowledge sharing, process optimization, and decision-making routines.

6. Mechanism and Robustness Tests

6.1. Mechanism Tests

Table 4 reports the mechanism and robustness results. Panel A shows that GenAI is positively associated with knowledge sharing, process optimization, and decision intelligence, with coefficients of 0.058, 0.064, and 0.071, respectively [2, 14]. These results indicate that firms with stronger generative AI disclosure tend to prioritize knowledge circulation, workflow improvement, and intelligent decision support.

After incorporating the three mechanism variables into the operational efficiency model, KS , PO , and DI all exhibit positive coefficients. Process optimization demonstrates the strongest effect, suggesting it may serve as the most direct channel through which generative AI enhances operational efficiency. These findings support the corresponding hypotheses.

6.2. Robustness Tests

Panel B reports a series of robustness checks. The core finding persists when substituting the generative AI dictionary, employing an alternative operational efficiency metric, using lagged GenAI , and omitting high-technology firms from the sample. Although statistical significance diminishes slightly in the lagged specification, the estimated coefficient remains positive and economically meaningful. Collectively, these analyses confirm that the observed positive association between generative AI disclosure and operational efficiency is not attributable to idiosyncratic choices in variable construction or sample composition [9].

Panel a. Mechanism Tests

Variable	KS	PO	DI	OE_{t+1}
$GenAI$	0.058**	0.064***	0.071***	0.026*
	(0.024)	(0.021)	(0.023)	(0.015)
KS				0.031*
				(0.017)
PO				0.044**
				(0.020)
DI				0.038**
				(0.018)
Controls	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	8,742	8,742	8,742	8,742
Adjusted (R^2)	0.317	0.342	0.328	0.436

Panel B. Robustness Tests

Test	Variable Adjustment	Coefficient of $GenAI$	Standard Error	Result
Alternative AI dictionary	Excluding "ChatGPT" and "DeepSeek"	0.039**	0.018	Supported
Alternative efficiency measure	Negative SG&A-to-sales ratio	0.041**	0.020	Supported
Lagged explanatory variable	Using $GenAI_{t-1}$	0.028*	0.016	Supported
Sample adjustment	Excluding high-technology firms	0.033**	0.015	Supported

Note: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

7. Conclusion

This study examines how generative AI contributes to firm operational efficiency in the context of digital transformation. Using SEC EDGAR 10-K annual reports as an open-source firm-level data source, the study constructs measures of generative AI disclosure intensity, digital transformation intensity, organizational mechanisms, and operational efficiency. The empirical results show that generative AI disclosure intensity is positively associated with subsequent operational efficiency. This finding suggests that firms paying greater attention to generative AI are more likely to improve operational outcomes through enhanced information processing, improved organizational coordination, and strengthened managerial decision support.

Mechanism tests indicate that knowledge sharing, process optimization, and decision intelligence are important channels through which generative AI enhances operational efficiency. Generative AI supports the transformation of fragmented information into reusable organizational knowledge, improves workflow coordination, and enables more structured and evidence-based operational decisions. Among these pathways, process optimization exhibits a relatively strong effect, suggesting that the operational value of generative AI is most directly realized in workflow improvement and coordination efficiency. Furthermore, digital transformation intensity moderates this relationship: firms with stronger digital transformation capabilities are better positioned to integrate generative AI into existing data systems, business platforms, and decision-making routines, thereby amplifying its efficiency-enhancing impact.

This study contributes to the literature in two ways. Theoretically, it advances the discussion of generative AI beyond broad technological application by examining its role in operational decision-making mechanisms. Practically, the findings suggest that firms should move beyond treating generative AI solely as a text generation tool and instead embed it systematically within knowledge management frameworks, process redesign initiatives, and intelligent decision-support systems.

This study also has limitations. Textual disclosure in regulatory filings cannot fully capture actual internal deployment or usage intensity of generative AI. Future research may combine public disclosures with surveys, interviews, or internal operational data to obtain more direct evidence on how generative AI reshapes enterprise operations.

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