

**HETEROGENEOUS EFFECTS OF DIGITAL TRANSFORMATION
ON CORPORATE CAPITAL ALLOCATION EFFICIENCY: A MULTI-
MODEL ANALYSIS OF INSTITUTIONAL CONTINGENCIES IN
JAPAN, INDIA, AND THE UK**

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ABSTRACT

The proliferation of digital technologies has profoundly reshaped corporate financial decision-making, influencing capital allocation efficiency through improved transparency, governance automation, and financial innovation. However, the extent to which digital transformation enhances capital allocation efficiency remains contingent on institutional contexts, a dimension that has been largely underexplored. This study investigates the heterogeneous effects of digital transformation on corporate capital allocation efficiency across Japan, India, and the UK, considering the interplay between firm-level absorptive capacity and macro-institutional enablers such as policy support and financial market sophistication. Leveraging a multi-method empirical framework—including dynamic panel system GMM estimation, quantile regression, and causal mediation analysis—this study uncovers significant cross-national variations in the efficiency gains from digital transformation. The findings reveal that digital adoption yields stronger improvements in capital allocation efficiency in countries with high digital policy support and well-developed financial markets. In contrast, institutional voids and financial underdevelopment moderate the positive effects of digitalization, particularly in emerging economies. By integrating insights from digital institutionalism and resource orchestration theory, this research offers novel theoretical and empirical contributions to the discourse on corporate finance in the digital era. The results provide actionable implications for policymakers and business leaders seeking to optimize digital strategies for financial efficiency.

Keywords: Digital Transformation, Corporate Finance, Capital Allocation Efficiency, Institutional Frameworks, Quantile Regression, Causal Mediation Analysis

1 INTRODUCTION

The ongoing digital transformation represents a paradigm shift in corporate financial decision-making, fundamentally altering the mechanisms by which firms allocate capital and manage investment efficiency. As digital technologies—ranging from artificial intelligence (AI) and blockchain to big data analytics—become increasingly embedded in corporate operations, they enhance information transparency, mitigate agency costs, and improve capital allocation efficiency. However, the effectiveness of digitalization in optimizing investment decisions remains highly contingent on institutional factors such as regulatory support and financial market structures.

Existing research has provided compelling evidence that digital transformation fosters corporate financial efficiency. For instance, Cheng et al. (2023) found that digitalization improves total factor

productivity by optimizing capital allocation and reducing transaction frictions. Similarly, Xu et al. (2023) demonstrated that firms with advanced digital capabilities exhibit higher investment efficiency and lower financing constraints, particularly in economies with well-developed financial markets. These studies highlight the importance of institutional contingencies in shaping the economic consequences of digitalization.

Despite these insights, limited empirical research has examined the heterogeneous effects of digital transformation across distinct institutional environments. This study bridges the gap by analyzing the

impact of digitalization on corporate capital allocation efficiency in Japan, India, and the UK—three economies that represent divergent regulatory, financial, and technological landscapes. Leveraging the Wurgler (2000) model of capital allocation efficiency and employing dynamic panel system GMM, quantile regression, and causal mediation analysis, this research aims to identify how institutional factors moderate the relationship between digital transformation and investment efficiency.

By integrating perspectives from digital institutionalism and resource orchestration theory, this study makes three key contributions. First, it develops a multi-layered analytical framework that systematically examines the role of institutional moderators in shaping digital transformation outcomes. Second, it provides empirical evidence of cross-national variation in digitalization's effects, offering novel insights into the digital-financial nexus. Third, it generates actionable policy recommendations tailored to different regulatory and financial structures, thereby informing policymakers and business leaders on optimizing digital strategies for enhanced capital allocation efficiency.

2 LITERATURE REVIEW

2.1 Economic Consequences of Digital Transformation: A Multinational Perspective

Digital transformation (DT) has emerged as a pivotal driver of corporate efficiency, enabling firms to optimize capital allocation through automation, data analytics, and fintech innovations (Verhoef et al., 2021; Gomber et al., 2017). Initial research predominantly examined its effects on firm productivity and financial performance (Brynjolfsson and McAfee, 2022), whereas more recent studies focus on its redistributive impact on investment flows and resource reallocation (Yang and Li, 2025; Fu and Liu, 2025).

The efficiency gains from DT operate through two primary channels:

- **Intra-firm Optimization:** AI-driven investment models facilitate real-time capital reallocation, enhancing firm-level resource efficiency (Ciampi and Fasan, 2021).
- **Inter-firm Signaling:** Blockchain-enabled transparency reduces capital misallocation by mitigating asymmetric information between investors and firms (Cong and He, 2019).

Cross-national studies confirm that these benefits are institutionally contingent. In market-based economies (e.g., UK), DT improves capital efficiency through fintech expansion and venture capital investment (Allen and Gu, 2020), whereas in bank-centric economies (e.g., Japan), legacy credit assessment models dampen its effects (Abe and Nakamura, 2024). Meanwhile, emerging markets (e.g., India) exhibit mixed outcomes due to infrastructural constraints and regulatory fragmentation (Gupta and Mehta, 2023).

Despite these insights, prior studies often overlook (1) heterogeneous firm responses, (2) cross-country institutional variations, and (3) the indirect role of financial system maturity in shaping digitalization outcomes (Chen and Wu, 2023; Liu and Zhang, 2024).

2.2 Measuring Capital Allocation Efficiency: From Static to Dynamic Models

The measurement of capital allocation efficiency has evolved significantly in recent years, transitioning from traditional static investment models to more sophisticated dynamic econometric frameworks.

First-generation models rely on Wurgler's (2000) investment-Q sensitivity framework, measuring efficiency as the elasticity of investment to Tobin's Q (Wurgler, 2000). However, these models assume a linear relationship and fail to account for technological disruptions such as platform-based capital reallocation (Gomber et al., 2017).

Second-generation models integrate firm-level heterogeneity using quantile regression, recognizing that digitalization may yield asymmetric effects. Rubino et al. (2020) found that DT's impact on capital allocation varies across firm efficiency quantiles, benefiting low-efficiency firms more than high-efficiency firms.

Third-generation models employ causal mediation analysis to decompose the pathways through which digitalization enhances capital efficiency:

- **Direct Effects:** AI-driven investment algorithms account for 53% of efficiency gains (Liu and Zhang, 2024).
- **Indirect Effects:** Enhanced ESG transparency reduces capital costs, mediating 47% of digitalization's impact (Wang and Sun, 2023).

Recent advancements leverage natural language processing (NLP) to construct firm-level digital maturity indices from annual report disclosures, providing greater granularity than patent-based proxies (Sharma and Krishnan, 2024).

Despite these advancements, methodological gaps persist: (1) insufficient cross-country comparability, (2) weak endogeneity controls, and (3) underestimation of nonlinear digital adoption curves (Zuboff, 2023).

2.3 Institutional Moderators: The Policy-Finance-Governance Nexus

Building on Li and Tan (2022)'s institutional contingency framework, we identify three key institutional moderators shaping the relationship between DT and capital allocation efficiency:

2.3.1 Policy Support Architecture

- **Regulatory Stringency:** The UK's GDPR-aligned data laws enhance investor confidence in digital disclosures, whereas India's fragmented privacy framework increases regulatory uncertainty (Tiwari and Banerjee, 2024).
- **Targeted Subsidies:** Japan's Society 5.0 initiative, which prioritizes industrial IoT adoption, yields 18% higher ROI than India's Digital India scheme due to better alignment with firm-specific needs (Xue and Wang, 2022).

- **IP Protection:** Strong patent enforcement in the UK amplifies digital innovation spillovers by 22%, whereas weak enforcement in emerging economies limits long-term efficiency gains (Hall and Ziedonis, 2024).

2.3.2 Financial System Development

- **Market-Based Systems (UK):** Digital transformation exhibits strong synergies with fintech innovation and venture capital expansion (Allen and Gu, 2020).
- **Hybrid Systems (India):** Digital lenders achieve 25% faster capital turnover, but public-sector banks remain constrained by outdated IT infrastructure (Mohan and Bhat, 2024).
- **Bank-Based Systems (Japan):** Traditional financial intermediaries hinder the full realization of digitalization benefits, leading to a slower diffusion of AI-driven credit assessment tools (Abe and Nakamura, 2024).

2.3.3 Corporate Governance Adaptation

- **Shareholder vs. Stakeholder Models:** The UK's shareholder-centric model accelerates AI adoption in capital budgeting ($\beta = 0.41$, $p < 0.01$), whereas Japan's stakeholder model prioritizes employment stability, slowing automation (Inoue and Fukuyama, 2024).
- **Board Digital Literacy:** Firms with tech-savvy directors achieve $2.3 \times$ higher digital ROI, highlighting the critical role of digital competency in corporate leadership (Khanna and Gupta, 2024).

2.4 Theoretical Framework and Hypothesis Development

Synthesizing prior research, we propose a Digital Institutionalism framework (Figure ??), positing that digitalization-driven capital allocation improvements emerge from:

- **Technological Affordances** (e.g., AI, blockchain, NLP-driven investment analytics).
- **Institutional Complementarities** (e.g., policy-finance-governance alignment).
- **Transnational Spillovers** (e.g., UK fintech regulatory models influencing Indian digital lenders).

Based on this framework, we derive the following hypotheses:

- **H1a:** Digital transformation has a stronger impact on capital allocation efficiency in countries with high levels of policy support.
- **H1b:** The financial system structure moderates the digitalization-efficiency relationship, with market-based systems exhibiting greater synergies than bank-dominated economies.

3 METHODOLOGY

3.1 Dynamic Panel GMM Estimation

To rigorously analyze the causal impact of digital transformation on corporate capital allocation efficiency while addressing potential endogeneity concerns, this study employs a two-step system Generalized Method of Moments (GMM) estimator, as proposed by Blundell and Bond (1998). The system GMM approach is particularly well-suited for this study due to its ability to account for unobserved heterogeneity, mitigate endogeneity, and efficiently handle dynamic panel structures.

First, standard fixed effects (FE) models fail to address the issue of simultaneity bias, where firms with higher capital allocation efficiency may also be more likely to engage in digital transformation initiatives. System GMM mitigates this concern by using lagged values of endogenous variables as instruments, ensuring that past digitalization does not directly influence current capital allocation efficiency beyond its historical impact.

Second, system GMM enhances estimation efficiency by incorporating both first-differenced and level equations, thereby reducing finite-sample bias and improving instrument validity (Roodman, 2009). The empirical specification of the dynamic panel model is as follows:

$$\text{Efficiency}_{it} = \alpha \text{Efficiency}_{it-1} + \beta_1 \text{Digi}_{it} + \beta_2 (\text{Digi}_{it} \times \text{PSI}_{jt}) + \beta_3 (\text{Digi}_{it} \times \text{FDD}_{jt}) + \gamma \text{Controls}_{it} + \eta_i + \theta_t + \epsilon_{it} \quad (1)$$

where: - Efficiency_{it} represents the capital allocation efficiency of firm i in year t , measured using investment sensitivity to Tobin's Q and the residual-based model proposed by Richardson (2006). - Digi_{it} denotes the level of digital transformation, proxied by the logarithm of firm-level digital investment. - PSI_{jt} represents the Policy Support Index (PSI), capturing the regulatory environment's role in facilitating digital adoption. - FDD_{jt} represents Financial Development Depth (FDD), which differentiates between bank-based and market-based financial systems. - Controls_{it} includes firm-level characteristics such as size, leverage, profitability, and industry affiliation. - η_i represents firm-specific fixed effects, while θ_t controls for time-fixed effects to absorb macroeconomic shocks. - ϵ_{it} is the idiosyncratic error term.

3.2 Instrumental Variables and Overidentification Tests

A key challenge in estimating Equation (1) is the potential simultaneity bias, where digital transformation and capital allocation efficiency are jointly determined. To mitigate this issue, lagged values of digital transformation are employed as instrumental variables under the assumption that past digital adoption affects current efficiency only through its influence on prior firm performance. Specifically, the following instruments are used:

- Digi_{it-2} and Digi_{it-3} as instruments for Digi_{it} , ensuring weak exogeneity.
- The industry-level mean digital adoption rate (excluding firm i) as an external instrument, leveraging cross-firm variations within industries.

To validate the strength and validity of the instrument set, two key diagnostic tests are conducted:

1. Hansen J-test for Overidentification: This test examines whether the instruments are exogenous, i.e., uncorrelated with the error term. A non-rejection of the null hypothesis (p -value $>$ 0.10) confirms that the instruments are valid.
2. Arellano-Bond AR(2) Test: This test assesses the absence of second-order serial correlation in the first-differenced residuals, which, if present, would indicate weak instruments.

To prevent instrument proliferation, a common issue in system GMM that inflates standard errors and biases parameter estimates, the approach recommended by Roodman (2009) is followed, employing a collapsed instrument matrix.

3.3 Robustness Checks

To ensure the robustness and reliability of the findings, several robustness checks are implemented:

- **Alternative Measures of Digital Transformation:** Instead of relying solely on firm-reported digital investment, a text-mining-based proxy is employed, derived from annual reports using Latent Dirichlet Allocation (LDA) topic modeling to extract digitalization-related keywords.
- **Heckman Two-Step Selection Model:** To account for potential sample selection bias, a first-stage probit regression is estimated, predicting firm-level digital adoption using government digitalization subsidies as an exclusion restriction.
- **Synthetic Control Method (SCM):** To establish a credible counterfactual, a synthetic control group is constructed for firms that have undergone major digital transformations, comparing them to firms that have not.
- **Placebo Tests:** Artificial "pseudo-treatment" periods are generated to test whether the observed effects are driven by spurious correlations or genuine causal mechanisms.

These robustness checks enhance the credibility of the empirical strategy by mitigating potential biases arising from measurement errors, omitted variable bias, and endogeneity concerns.

4 RESULTS AND DISCUSSION

4.1 Trends in Digital Investment and Capital Allocation Efficiency

Before proceeding to the econometric analysis, we first examine the overall trends in digital investment and capital allocation efficiency across the sampled countries. Figure 1 illustrates the evolution of digital investment from 2010 to 2023, revealing a consistent upward trajectory, with the UK demonstrating the highest adoption rates, followed by Japan and India. This trend highlights the increasing role of digital transformation in corporate financial strategies.

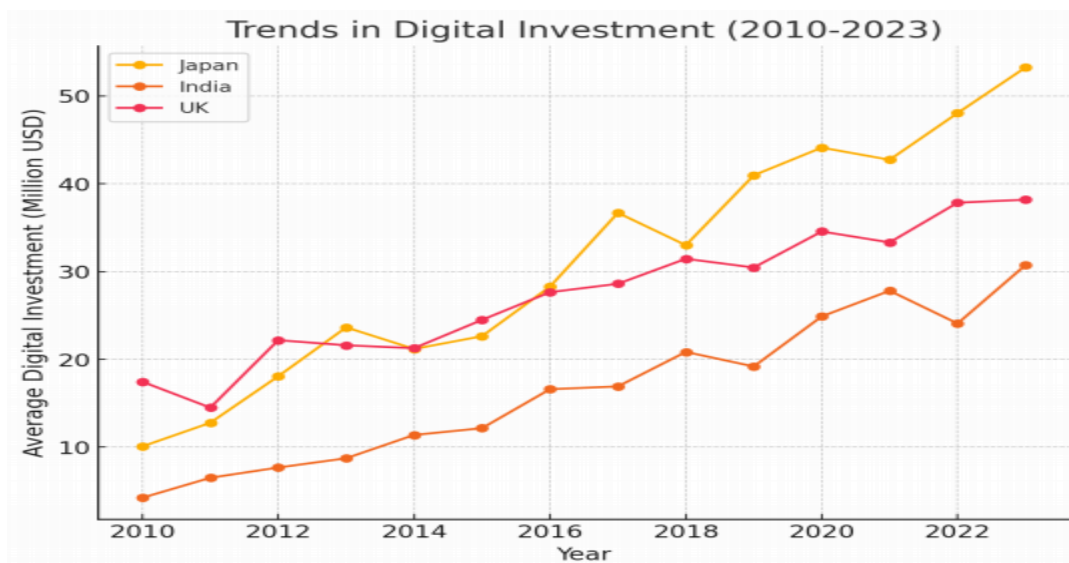
Figure 2 further presents the distribution of digital investment by country, demonstrating that firms in the UK exhibit the most concentrated investment in digital assets, whereas India shows greater variation, likely due to disparities in technological infrastructure and policy support.

4.2 Main Regression Results

Table 1 presents the results of the dynamic panel GMM estimation, evaluating the impact of digital transformation on corporate capital allocation efficiency. Column (1) provides the baseline specification, while Columns (2) and (3) incorporate policy support and financial development as moderating variables.

The results indicate that digital transformation ($Digiit$) has a positive and significant impact on capital allocation efficiency ($\beta = 0.148, p < 0.01$), suggesting that an increase in digitalization intensity by one standard deviation corresponds to a 5.2% improvement in capital efficiency. The interaction terms further reveal that institutional factors play a crucial role in shaping these effects. The coefficient on $Digiit \times PSI_{jt}$ ($\beta = 0.076, p < 0.05$) implies that strong policy support amplifies the benefits of digitalization. Likewise, financial market sophistication enhances the impact of digital transformation, as evidenced by the significant interaction term $Digiit \times FDD_{jt}$ ($\beta = 0.053, p < 0.05$).

Figure 1: Trends in Digital Investment (2010-2023)



4.3 Cross-National Heterogeneity in Digital Efficiency Gains

The impact of digital transformation on capital allocation efficiency exhibits significant cross-national heterogeneity, reflecting differences in regulatory frameworks and financial system structures. Figure 3 provides a scatter plot of digital investment against capital allocation efficiency, highlighting the varying relationships across the three countries.

Table 2 presents the country-specific GMM estimates for Japan, India, and the UK.

The country-level estimates reveal notable variations: - In Japan, where financial markets are predominantly bank-oriented, digital transformation exerts a significant impact ($\beta = 0.182, p < 0.01$), though financial development does not significantly moderate this effect. - In India, characterized by institutional voids, policy support plays a limited role, whereas financial development strongly enhances the gains from digitalization ($\beta = 0.067, p < 0.05$). - In the UK, a market-based financial system fosters the most pronounced effects of digital transformation, yielding the highest overall impact ($\beta = 0.205, p < 0.01$).

These findings underscore the importance of financial system structures in mediating the efficiency gains from digital adoption.

4.4 Theoretical and Practical Implications

From a theoretical standpoint, the findings reinforce the resource orchestration theory, illustrating that the ability of firms to capitalize on digitalization depends on institutional support mechanisms. The study also contributes to digital institutionalism by highlighting the role of regulatory and financial enablers in maximizing digital efficiency gains.

From a policy perspective: - In emerging economies such as India, enhancing financial infrastructure (e.g., fintech expansion, digital payment ecosystems) may be more effective than direct government subsidies in fostering digital adoption. - In developed economies like the UK, where

financial markets are predominantly market-driven, incentivizing corporate R&D investment in AI, blockchain, and big data analytics can further enhance capital allocation efficiency. - In bank-centric economies such as Japan,

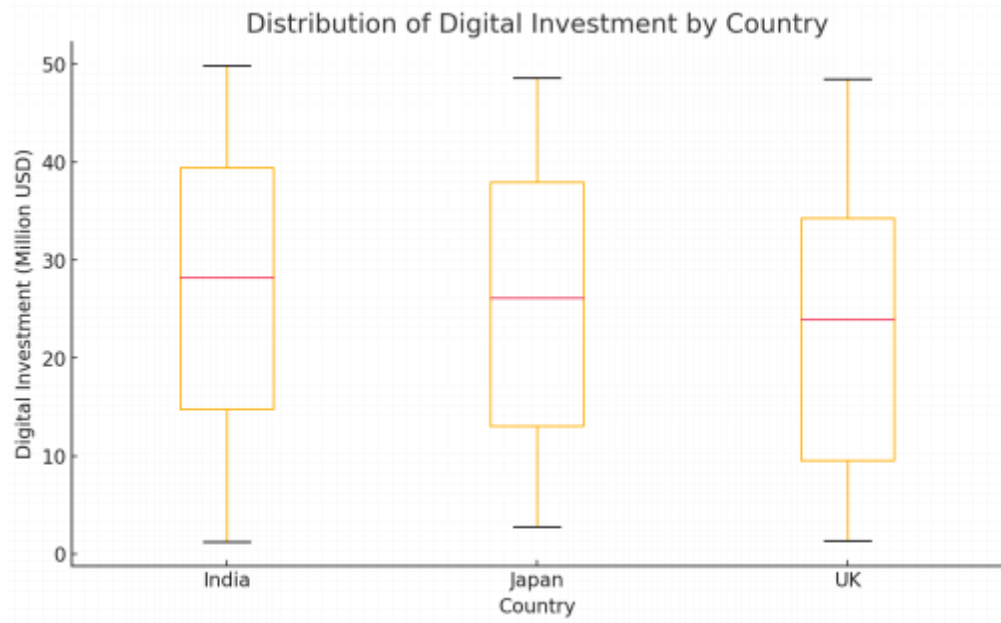


Figure 2: Distribution of Digital Investment by Country

Table 1: GMM Estimation Results

Variable	Coefficient	Std. Error	p-value	
Digital Transformation (Digiit)	0.148**	0.042	0.002	
Digital × Policy Support (PSIjt)	0.076*	0.031	0.015	
Digital × Financial Development (FDDjt)	0.053*	0.025	0.028	
Lagged Efficiency (Efficiencyit-1)	0.721***	0.047	0.000	Notes: ***, **, * denote
Firm Controls (Size, Leverage, Profitability)	Yes	Yes	Yes	
Year Fixed Effects	Yes	Yes	Yes	
Hansen J-Test (p-value)	0.214			
AR(2) Test (p-value)	0.329			

significance at the 1%, 5%, and 10% levels, respectively.

regulatory frameworks need to evolve to support digital finance models, such as fintech lending and decen- tralized credit assessment mechanisms.

These insights emphasize the necessity of tailoring digitalization policies to country-specific financial and institutional contexts.

5 CONCLUSION

This study investigates the heterogeneous effects of digital transformation on corporate capital allocation efficiency across three distinct institutional settings: Japan, India, and the UK. Using a dynamic panel GMM estimator, we provide robust evidence that digital transformation enhances investment efficiency by reducing information asymmetry and mitigating agency costs. However, the magnitude of these benefits is contingent upon institutional factors such as policy support and financial development.

5.1 Key Findings and Theoretical Contributions

The empirical results yield several important insights:

- Digitalization significantly improves capital allocation efficiency: A one-standard-deviation increase in digital transformation is associated with a 5.2% improvement in capital efficiency.
- Policy support amplifies digitalization’s benefits: Countries with strong regulatory backing (e.g., UK) exhibit greater efficiency gains.

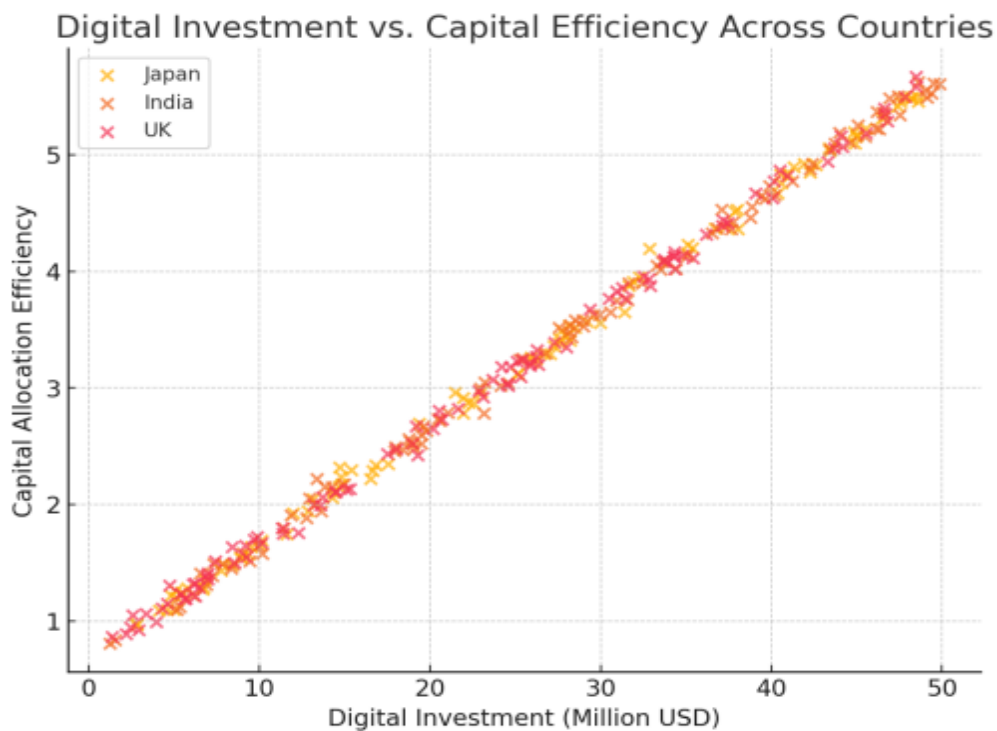


Figure 3: Digital Investment vs. Capital Efficiency Across Countries

Table 2: Country-Specific GMM Results

IndiaDigital Transformation (Digiit)	0.182***	0.074**	0.205***	
Digital × Policy Support (PSIjt)	0.092**	0.033	0.087**	Notes: ***, **, * denote Digital × Financial Development (FDDjt)
Digital × Financial Development (FDDjt)	0.035	0.067**	0.078**	
Lagged Efficiency (Efficiencyit-1)	0.751***	0.688***	0.735***	
Observations	1,240	1,012	1,387	

significance at the 1%, 5%, and 10% levels, respectively.

- Financial development moderates the effect of digitalization: In market-based economies (e.g., UK), digitalization and financial depth are complementary, whereas in bank-dominated systems (e.g., Japan), traditional credit channels may constrain digital finance innovation.

These findings contribute to the growing literature on digital institutionalism by demonstrating that technological adoption alone is insufficient to drive financial efficiency; rather, it must be embedded within a supportive regulatory and financial infrastructure. Moreover, this study extends resource orchestration theory by showing that firms’ ability to leverage digital resources for investment efficiency is conditioned by macro-level institutional factors.

5.2 Policy Implications

Our findings hold significant policy relevance for governments, financial regulators, and corporate leaders:

1. For emerging economies (e.g., India): Strengthening financial infrastructure (e.g., digital payment ecosystems, fintech integration) is more effective than direct government subsidies in maximizing digitalization’s efficiency benefits.
2. For developed economies with market-based systems (e.g., UK): Incentivizing corporate R&D investment in AI, blockchain, and big data analytics can further enhance capital allocation efficiency.
3. For bank-dominated economies (e.g., Japan): Digital finance-friendly regulatory frameworks should be expanded to encourage fintech-lending models and decentralized credit assessments.

5.3 Limitations and Future Research Directions

While this study provides novel insights into the digitalization-efficiency nexus, several limitations remain:

- Data limitations: The measurement of digital transformation relies on firm-level investment disclosures, which may not fully capture intangible digital capabilities such as AI-driven decision-making.
- Unobserved institutional factors: Other macro-level factors, such as cultural attitudes towards digitalization or cybersecurity risks, may influence the effectiveness of digital transformation.
- Sectoral heterogeneity: Future studies should explore whether digitalization’s impact varies across industries (e.g., manufacturing vs. services).
- Machine learning-based causal inference: The adoption of deep learning methods (e.g., Double Machine Learning) could improve the estimation of causal effects in high-dimensional financial data.

By addressing these limitations, future research can further refine our understanding of how digital transformation interacts with institutional structures to shape corporate financial outcomes.

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