http://dx.doi.org/10.18623/rvd.v23.5842

DIGITAL TRANSFORMATION AND FIRM PERFORMANCE IN CHINESE MANUFACTURING

TRANSFORMAÇÃO DIGITAL E DESEMPENHO DE EMPRESAS NA MANUFATURA CHINESA

Article received on: 12/14/2025
Article accepted on: 3/14/2026

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The authors declare that there is no conflict of interest

Abstract
Digital transformation is becoming a strategic priority for manufacturing firms. However, existing research often treats it as a broad phenomenon, failing to examine differences in the depth of transformation. Therefore, this study introduces the concept of Digital Transformation Degree (DTD) and develops an empirical model based on the TOE framework (Technological, Organizational, Environmental factors). Using survey data from 377 Chinese manufacturing firms and PLS-SEM analysis, the authors examined what drives DTD and how it affects innovation performance (IP) and firm performance (FP). Results show that technological and environmental factors significantly enhance DTD. However, organizational factors do not. Moreover, DTD positively influences both IP and FP, with IP partially mediating the relationship between DTD and FP. These findings highlight that not all TOE dimensions contribute equally to digital transformation, and that innovation is a key pathway through which digital depth creates organizational value. Finally, the study offers manufacturing firms practical guidance, seeking to deepen their digital transformation and convert it into measurable performance gains.

Resumo
A transformação digital está se tornando uma prioridade estratégica para as empresas manufatureiras. No entanto, a pesquisa existente frequentemente a trata como um fenômeno amplo, deixando de examinar as diferenças na profundidade da transformação. Portanto, este estudo introduz o conceito de Grau de Transformação Digital (DTD) e desenvolve um modelo empírico baseado no framework TOE (fatores Tecnológicos, Organizacionais e Ambientais). Utilizando dados de survey de 377 empresas manufatureiras chinesas e análise PLS-SEM, os autores examinaram o que impulsiona o DTD e como ele afeta o desempenho de inovação (IP) e o desempenho da empresa (FP). Os resultados revelaram que os fatores tecnológicos e ambientais melhoram significativamente o DTD. No entanto, os fatores organizacionais não o fazem. Além disso, o DTD influencia positivamente tanto o IP quanto o FP, com o IP mediando parcialmente a relação entre DTD e FP. Esses achados destacam que nem todas as dimensões do TOE contribuem igualmente para a transformação digital, e que a inovação é um caminho fundamental através do qual a profundidade digital cria valor para a empresa. O estudo oferece orientações práticas para empresas manufatureiras que buscam

Keywords: Digital Transformation. Firm Performance. Innovation. Manufacturing. Toe Framework.

aprofundar a transformação digital e convertê-la em ganhos mensuráveis de desempenho.

Palavras-chave: *Desempenho de Empresas. Inovação. Manufatura. Transformação Digital. Framework Toe.*

1 INTRODUCTION

Digital transformation is now a central concern for manufacturing firms, as technologies such as big data analytics, cloud computing, artificial intelligence (AI), and the industrial internet of things (IoT) are becoming widespread. Therefore, manufacturers can no longer rely on isolated technological upgrades. instead, organizations must reconsider how operations are coordinated, how resources are deployed, and how value is created across the entire organization.

However, the academic literature often discusses digital transformation in broad terms, focusing mainly on whether firms adopt digital technologies. This approach overlooks an important reality: some firms digitalize only selected functions, while others develop deep, integrated transformations that affect coordination, decision-making, and value creation across the entire organization. A degree-based perspective is more useful than a simple adoption perspective.

This study identifies three research gaps. First, existing studies have not paid sufficient attention to the *degree* of digital transformation as distinct from mere adoption. Second, prior research often examines either the antecedents of digital transformation or its outcomes, but rarely links both sides within a single empirical framework. Third, although innovation is frequently mentioned as a benefit of digitalization, the specific mechanism by which the degree of digital transformation translates into firm performance – particularly the mediating role of innovation performance – remains underexplored in the manufacturing context. This gap is especially significant for Chinese manufacturing firms, which face strong pressures to upgrade their technology and renew their innovation.

Therefore, this study adopts the concept of the Digital Transformation Degree (DTD) to capture the extent and systematicity of digital technology embedding in manufacturing firms. We ground our investigation in the TOE (Technology-Organization-Environment) framework, which provides a well-established lens for explaining organizational responses to technological change.

The research objectives (ROs) are:

RO1: To identify the technological, organizational, and environmental factors that drive the degree of digital transformation in Chinese manufacturing firms.

RO2: To assess whether a higher degree of digital transformation improves innovation performance and overall firm performance.

RO3: To test whether innovation performance mediates the relationship between digital transformation degree and firm performance.

The corresponding research questions (RQs) are:

RQ1: What factors drive DTD in Chinese manufacturing firms?

RQ2: Does DTD improve innovation performance and firm performance?

RQ3: Does innovation performance mediate the relationship between DTD and firm performance?

This study makes three contributions. First, it advances the literature by emphasizing DTD rather than treating digital transformation as a binary outcome. Second, it integrates TOE factors, DTD, innovation performance, and firm performance into a single empirical framework. Third, it clarifies the mechanism through which digital depth translates into firm value – specifically, via innovation performance as a partial mediator.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes the methodology. Section 4 presents the results. Section 5 discusses the findings, and Section 6 offers a conclusion.

2 LITERATURE REVIEW

2.1 Digital transformation degree (DTD) in manufacturing

Digital transformation in manufacturing is commonly associated with Industry 4.0 technologies. Existing studies agree that these technologies can improve efficiency, flexibility, and responsiveness, but such improvements depend heavily on how digital initiatives are implemented (Buer et al., 2021. Li et al., 2025. Wang et al., 2023). Some manufacturers digitalize only limited operations, while others move towards integrated transformation affecting coordination, information sharing, decision processes, and performance management (Daud, 2024. Eller et al., 2020). Moreover, Industry 4.0 research on implementation, digital maturity, and technology-enabled organizational change shows that organizations differ substantially in how deeply digital technologies are embedded in everyday routines and managerial systems (Li et al., 2025. Yang & Yee, 2022). Therefore, this study uses DTD to capture that depth.

2.2 TOE framework as antecedents of DTD

The TOE framework offers suggestions for why organizations differ in their digital transformation trajectories, as technological, organizational, and environmental factors jointly shape a firm's response to technological change (Baker, 2012).

Technological factors (TF) include technological readiness (digital infrastructure), IT capability (ability to deploy and integrate digital technologies), and technological complexity (ability to cope with implementation challenges) (Shahadat et al., 2023). In manufacturing, deeper transformation requires more than access to tools. firms must be prepared to integrate technologies into production systems and managerial processes (Agustian et al., 2023. Chen & Tian, 2022. Tian et al., 2023).

Organizational factors (OF) include top management support, organizational learning capability, and organizational flexibility. Digital transformation often requires strategic commitment, knowledge sharing, and structural adaptation (López-Muñoz & Escribá-Esteve, 2022). Even with available technologies, transformation is unlikely to deepen without supportive organizational arrangements (Zhang & Yang, 2023). Some studies suggest that organizational factors become relevant only after basic technological readiness is established (Chen, 2023). In manufacturing environments with uneven digital maturity, top management support and learning capability may not differentiate firms as clearly as access to technology does.

Environmental factors (EF) include competitive pressure (Cenci et al., 2025), regulatory support and pressure (Akhtar et al., 2024), and environmental uncertainty (Wang et al., 2023). Manufacturing firms do not pursue digital transformation in isolation.

market competition, policy signals, and external instability influence the perceived need for digitalization (Chen & Tian, 2022. Dai & Fang, 2024. Zhu et al., 2023).

Based on the TOE framework, we propose:

H1. Technological Factors (TF) positively influence Digital Transformation Degree (DTD).

H2. Organizational Factors (OF) positively influence Digital Transformation Degree (DTD).

H3. Environmental Factors (EF) positively influence Digital Transformation Degree (DTD).

2.3 Digital transformation degree (DTD), innovation performance (IP), and firm performance (FP)

A high degree of digital transformation has been reported to influence both innovation and performance positively. With embedded digital technologies, firms can improve information visibility, data-based decision-making, and cross-functional collaboration. These are all conditions that favor product, process, and organizational innovation (Liang & Li, 2022. Shah et al., 2024. Xu et al., 2024). Multiple studies have shown that AI innovation depends not only on technology adoption but also on how organizations share knowledge, learn, manage talent, and use external ties (Liu & Li, 2025. Zhao et al., 2026). Prior research also suggests that digital capabilities enhance innovation outcomes by facilitating knowledge integration and learning (Chen & Kim, 2023. Wang & Zhang, 2025). Accordingly:

H4. Digital Transformation Degree (DTD) positively influences Innovation Performance (IP).

Digital transformation also contributes directly to organizational performance by improving coordination, efficiency, flexibility, and responsiveness. In manufacturing, deeper transformation supports better resource allocation, reduced information delays, improved process control, and faster responses to market demands (Guo & Xu, 2021. Yang & Yee, 2022. Li et al., 2023). Firms with more advanced and systematic digital transformation are more likely to realize tangible performance gains. Accordingly:

H5. Digital Transformation Degree (DTD) positively influences Firm Performance (FP).

Innovation performance itself is a driver of firm performance. Better product, process, and organizational innovation lead to upgraded production, refined offerings, and new solutions that respond to customer needs and technological change (Chen & Kim, 2023. Liang & Li, 2022. Xu et al., 2024). Therefore:

H6. Innovation Performance (IP) positively influences Firm Performance (FP).

2.4 The mediating role of innovation performance (IP)

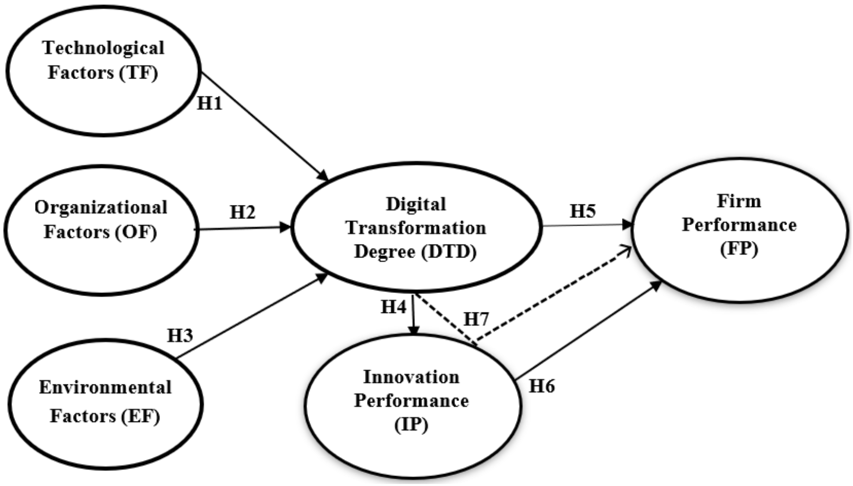
Digital transformation often changes how information is shared, how departments coordinate, and how problems are solved. These changes may first strengthen the firm's ability to innovate. the benefits of that improvement then translate into broader firm-level outcomes. This makes IP a plausible mediating mechanism (Chen & Kim, 2023. Yang & Yee, 2022). When digital technologies are deeply embedded, firms collect and use real-time information, improve coordination, and support systematic experimentation – all of which strengthen IP, which in turn contributes to higher FP (Chen & Kim, 2023). Therefore:

H7. Innovation Performance (IP) mediates the relationship between Digital Transformation Degree (DTD) and Firm Performance (FP).

Figure 1 presents the conceptual model.

Figure 1

Conceptual Model



3 METHODS

3.1 Research design and sample

This study used a quantitative, cross-sectional survey design. The target population was Chinese manufacturing firms (Li & Branstetter, 2024). Respondents were middle- - and senior-level managers (general managers, department heads, production managers, IT managers, R&D managers) who had a clear understanding of their firms' digital transformation practices and performance.

Data were collected through online and paper-based questionnaires. After screening for incomplete responses, 377 valid responses were collected. The sample characteristics were as follows. Of the 377 respondents, 55.2% were male—most held master's degrees (36.6%) or doctorates (31.0%). Participating firms were primarily private enterprises (59.4%) in equipment manufacturing (37.4%), with a broad geographic distribution across Eastern (39.5%), Central (33.2%), Western (17.0%), and Northeastern China (10.3%). Most firms had been operating for more than 11 years (73.5%). This distribution provides a solid basis for examining the proposed relationships.

3.2 Measurement

All constructs were measured using five-point Likert scales (1 = strongly disagree to 5 = strongly agree), with survey items adapted from previously validated studies. To illustrate:

1) Technological readiness was measured with items such as “Our firm has the necessary digital infrastructure” and “Our IT systems are compatible with new technologies.”
2) IT capability included “Our IT department can effectively integrate new digital tools” and “We have skilled personnel to manage digital systems.”
3) Top management support included “Senior leaders actively promote digital transformation” and “Management allocates sufficient resources for digital initiatives.”
4) DTD was assessed through three dimensions: digital infrastructure and system integration (e.g., “Digital systems are integrated across departments”), data-driven decision making (e.g., “Data analytics supports daily decision making”), and business process digitalization (e.g., “Our core processes have been digitized end-to-end”).
5) Innovation performance (IP) covered product innovation (e.g., “Our firm frequently introduces new products”), process innovation (e.g., “We have improved production processes significantly”), and organizational innovation (e.g., “We have adopted new management practices”).
6) Firm performance (FP) included financial performance (e.g., “Profitability has improved”), market performance (e.g., “Market share has grown”), and operations performance (e.g., “Operational efficiency has increased”).

All items used the same five-point scale. The questionnaire was reviewed for clarity and contextual fit before distribution.

3.3 Data analysis

The study used SPSS for descriptive statistics (Pimdee & Leekitchwatana, 2022) and SmartPLS for Partial Least Squares Structural Equation Modeling (PLS-SEM)

(Sarstedt et al., 2024). PLS-SEM is appropriate for complex models with mediation and a prediction-oriented focus. The analysis followed two steps: measurement model assessment (reliability, convergent validity, discriminant validity) and structural model assessment (path coefficients, R^2, effect sizes, mediation).

4 RESULTS

4.1 Firm characteristics

Table 1 shows that most firms had between 50–99 employees (36.3%). Quite interestingly, most firms were over 20 years old (39.0%), and 59.4% were privately owned. Moreover, 37.4% indicated they were in the equipment manufacturing sector. Not surprisingly, 39.5% indicated they were located in Eastern China.

Table 1

Descriptive Statistics of Firm Characteristics (n=377)

Variable	Item	Frequency	Percent
B1 (Firm Size)	Less than 50 employees	31	8.2
	50–99	137	36.3
	100–299	94	24.9
	300–999	75	19.9
	1,000 or more	40	10.6
B2 (Firm Age)	Less than 5 years	15	4.0
	5–10 years	85	22.5
	11–20 years	130	34.5
	More than 20 years	147	39.0
B3 (Ownership Type)	State-owned enterprise	38	10.1
	Private enterprise	224	59.4
	Foreign-invested enterprise	41	10.9
	Joint venture	54	14.3
	Other	20	5.3
B4 (Industry Sector)	Equipment manufacturing	141	37.4
	Electronics and electrical manufacturing	62	16.4
	Automotive and parts manufacturing	91	24.1
	Chemical and materials manufacturing	46	12.2
	Other manufacturing industry	37	9.8
B5 (Region)	Eastern China	149	39.5
	Central China	125	33.2
	Western China	64	17.0
	Northeastern China	39	10.3

4.2 Measurement model

The measurement model was assessed for reliability, convergent validity, and discriminant validity before testing the structural relationships. All constructs demonstrated satisfactory psychometric properties.

4.2.1 Reliability and convergent validity

Each construct's Cronbach's alpha ranged from 0.710 to 0.791 and exceeded the recommended threshold of 0.70. This then indicated a good internal consistency. Composite reliability (rho_c) values were also all above 0.83, further confirming reliability. Convergent validity was assessed using average variance extracted (AVE). All AVE values exceeded 0.63, well above the minimum acceptable level of 0.50 (Ahmad et al., 2023). In addition, all indicator loadings were above 0.70 (the lowest was 0.748), confirming that each item adequately represented its intended construct. These results, presented in Table 2, demonstrate that the measurement model meets established guidelines for reliability and convergent validity (Lim, 2024).

Table 2

Reliability and Convergent Validity (summary)

Construct	Cronbach's α	rho_c	AVE
Technological readiness	0.728	0.846	0.648
IT capability	0.721	0.843	0.642
Technological complexity	0.761	0.863	0.677
Top management support	0.759	0.861	0.674
Organizational learning capability	0.759	0.862	0.675
Organizational flexibility	0.791	0.878	0.705
Competitive pressure	0.719	0.842	0.641
Regulatory support/pressure	0.737	0.851	0.656
Environmental uncertainty	0.764	0.864	0.679
DTD – infrastructure	0.741	0.853	0.658
DTD – data-driven	0.726	0.846	0.646
DTD – process	0.721	0.843	0.642
IP – product	0.735	0.850	0.654
IP – process	0.764	0.864	0.680
IP – organizational	0.729	0.847	0.649
FP – financial	0.779	0.872	0.694
FP – market	0.710	0.838	0.634
FP – operations	0.745	0.855	0.662

Note: All indicator loadings >0.70. all AVE >0.50.

4.2.2 Discriminant validity

We used the heterotrait-monotrait (HTMT) criterion to assess whether the constructs are empirically distinct. All HTMT values were below the strict threshold of 0.85 (Dirgiatmo, 2023), confirming that each construct shares more variance with its own indicators than with other constructs. The highest HTMT value was 0.829, observed between organizational learning capability and organizational flexibility, still acceptably below the cutoff. For brevity, the full HTMT matrix is available from the authors upon request.

4.3 Structural model

4.3.1 Preliminary checks

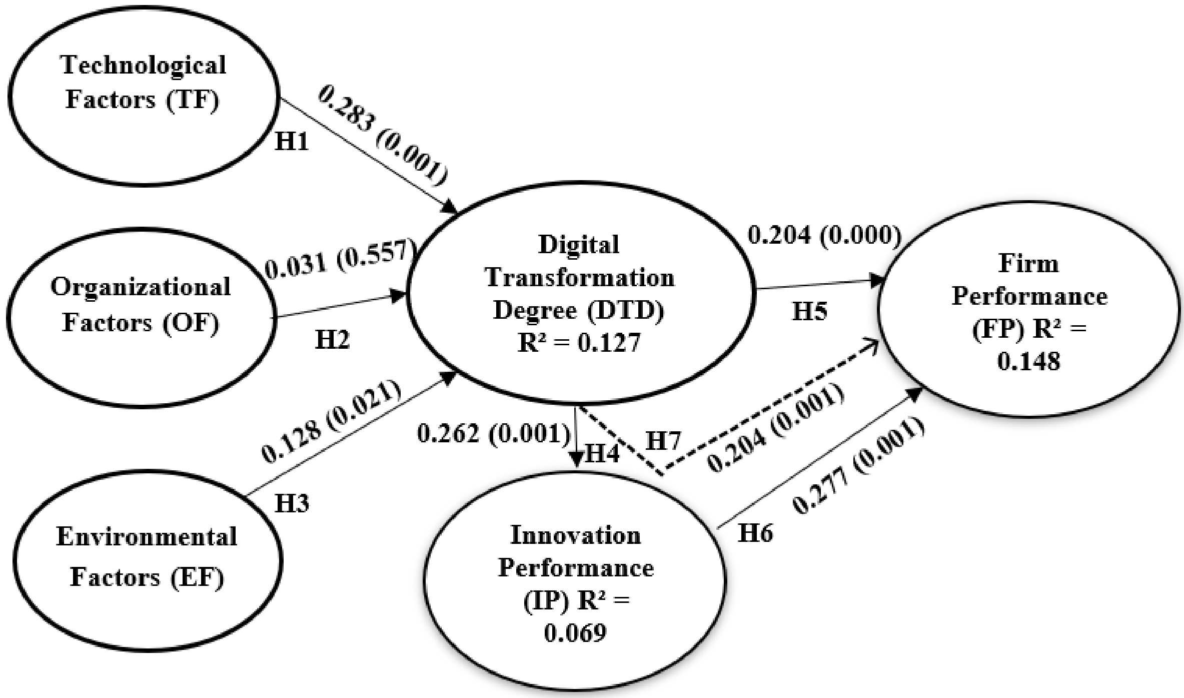
Before testing the hypotheses, we examined common method bias and collinearity. Harman's single-factor test extracted the first factor accounting for only 18.15% of the total variance, well below the 40% threshold. This suggests that common method bias is unlikely to distort the results. We also computed variance inflation factors (VIF) for all predictor constructs. VIF values ranged from 1.000 to 1.200, all far below the conservative cutoff of 3.0, indicating no problematic multicollinearity among the independent variables.

4.3.2 Hypothesis testing

Figure 2 presents the structural model results with standardized path coefficients and explained variances (R^2). Table 3 reports the detailed path coefficients, t-values, significance levels, and R^2 values for the endogenous variables.

Figure 2

Structural Model Results



Note: R^2: DTD = 0.127. R^2: IP = 0.069. R^2: FP = 0.148.

As shown in Table 3, technological factors (β = 0.283, p < 0.001) and environmental factors (β = 0.128, p = 0.021) have significant positive effects on DTD, supporting H1 and H3. However, organizational factors do not significantly influence DTD (β = 0.031, p = 0.557). thus, H2 is not supported. DTD has a significant positive effect on innovation performance (β = 0.262, p < 0.001) and on firm performance (β = 0.204, p < 0.001), supporting H4 and H5. Finally, innovation performance positively affects firm performance (β = 0.277, p < 0.001), supporting H6.

The R^2 values indicate that the three TOE factors collectively explain 12.7% of the variance in DTD. DTD explains 6.9% of the variance in IP, and together DTD and IP explain 14.8% of the variance in FP. These values are modest but acceptable for exploratory research on organizational-level constructs, especially given PLS-SEM's prediction-oriented nature.

Table 3

Path Coefficients, Mediation, and R²

Relationship	Effect	t-value	p	Decision
TF → DTD	0.283	5.251	<0.001	Supported
OF → DTD	0.031	0.587	0.557	Not supported
EF → DTD	0.128	2.303	0.021	Supported
DTD → IP	0.262	5.613	<0.001	Supported
DTD → FP	0.204	4.112	<0.001	Supported
IP → FP	0.277	5.397	<0.001	Supported
DTD → FP (direct)	0.204	4.112	<0.001	–

R^2 DTD = 0.127. R^2 IP = 0.069. R^2 FP = 0.148

4.4 Mediation analysis (H7)

To test whether IP mediates the relationship between DTD and FP, we examined the indirect effect. The indirect effect of DTD on FP via IP is significant ($\beta = 0.072$, $t = 3.778$, $p < 0.001$). The direct effect of DTD on FP remains significant ($\beta = 0.204$, $p < 0.001$) after including the mediator. This pattern indicates partial mediation – DTD improves FP both directly and indirectly through enhanced innovation performance. Thus, H7 is supported.

4.5 Predictive relevance and effect sizes

We assessed the model's predictive relevance using Stone-Geisser's Q^2. All Q^2 values for endogenous constructs were positive: DTD = 0.055, IP = 0.031, FP = 0.067. This confirms that the model has acceptable predictive relevance for each endogenous variable. Effect sizes (f^2) indicate the relative contribution of each predictor. The f^2 values for the supported paths were small but meaningful: TF → DTD (0.082), DTD → IP (0.074), and IP → FP (0.084). The effect of EF → DTD (0.016) falls below the conventional threshold for a small effect, while OF → DTD (0.001) is negligible. These effect sizes suggest that although the relationships are statistically significant, their practical impact is limited – a common finding in complex organizational research.

In summary, the structural model supports six of the seven hypotheses (Table 4). The only unsupported hypothesis is H2, which suggests that, in this sample of Chinese manufacturing firms, organizational factors do not independently drive the degree of digital transformation. The mediation analysis confirms that innovation performance serves as a partial mechanism linking DTD to firm performance.

Table 4

Summary of Hypothesis Testing Results

Hyp.	Path	Result
H1	Technological factors → DTD	Supported
H2	Organizational factors → DTD	Not supported
H3	Environmental factors → DTD	Supported
H4	DTD → Innovation performance	Supported
H5	DTD → Firm performance	Supported
H6	Innovation performance → Firm performance	Supported
H7	IP mediates DTD → FP	Supported (partial mediation)

5 DISCUSSION

This study examined the drivers of the degree of digital transformation in Chinese manufacturing and how DTD affects innovation and firm performance. The results offer several insights.

First, technological and environmental factors significantly enhance DTD, but organizational factors do not. This finding suggests that in the current sample, having the right technology infrastructure and facing external pressures (competition, regulation, uncertainty) matters more for deepening digital transformation than internal organizational conditions alone. This aligns with recent TOE-based studies in emerging economies (Alkhatib et al., 2025. Zhu et al., 2023). The non-significant effect of organizational factors was unexpected but informative. One explanation is that in Chinese manufacturing, many firms are at early or intermediate stages of digital transformation, where access to technology and external pressure matter more than internal organizational characteristics (Shah et al., 2024). Another possibility is that organizational learning and flexibility enable transformation only when combined with strong technological foundations – an interaction effect not tested here. Future research should examine whether organizational factors moderate rather than directly drive DTD.

Second, DTD improves both innovation performance and firm performance. This confirms that digital transformation should not be viewed as simple technology adoption. When firms achieve deeper integration of digital tools into operations and management, they are better able to coordinate, use information, and respond, which supports innovation and overall performance. The positive effect of IP on FP reinforces the idea that innovation remains a key channel for translating transformation efforts into tangible gains (Chen & Kim, 2023).

Third, IP partially mediates the DTD–FP relationship. This is a nuanced finding: part of the value of digital depth is direct (efficiency, coordination, responsiveness), and part is indirect through better innovation outcomes. For managers, this means that digital transformation initiatives should be explicitly linked to innovation objectives. Simply digitizing existing processes without fostering innovation may leave performance gains on the table (Chen & Kim, 2023).

Theoretical implications: These findings extend the TOE framework by showing that its three dimensions do not operate with equal strength in the manufacturing context. They also contribute to the digital transformation literature by shifting focus from binary adoption to degree, and by identifying a specific mechanism (innovation) through which digital depth creates value. Our results partially support the dynamic capabilities view: digital depth enables sensing, seizing, and reconfiguring, which, in turn, manifests as innovation performance (Li et al., 2025).

Practical implications: Manufacturing firms should prioritize building technological readiness and IT capability, and they should pay attention to competitive and regulatory pressures as drivers of deeper transformation. However, technology alone is insufficient. firms must also align digital efforts with innovation goals. Leaders should ask not only “Are we digitizing?” but “How deeply are we digitizing, and is that depth translating into new products, processes, and organizational improvements?”

Limitations and future research: Several limitations should be acknowledged. First, the cross-sectional design prevents strong causal claims. longitudinal data would better establish directionality. Second, all measures were self-reported by managers, raising the potential for common method bias, though Harman's test suggested this was not a serious issue. Third, the sample is limited to Chinese manufacturing. findings may not generalize to other sectors or countries (Chen & Tian, 2022). Fourth, the modest R^2 values indicate that other important drivers of digital transformation – such as digital strategy, workforce skills, or supply chain integration – were not included. Future research could use longitudinal designs, compare multiple countries, or include additional mediators and moderators.

6 CONCLUSIONS

This study examined the relationships among TOE factors, the degree of digital transformation, innovation performance, and firm performance in Chinese manufacturing. Using survey data from 377 firms and PLS-SEM analysis, we found that technological and environmental factors drive DTD, whereas organizational factors do not have a significant effect. DTD improves both innovation and firm performance, and innovation performance partially mediates the link between DTD and firm performance.

The study contributes to theory by extending the TOE framework to a degree-based conceptualization of digital transformation and by clarifying the mediating role of innovation. For practice, manufacturing firms should strengthen their technological foundations, respond to external pressures, and align digital transformation with innovation objectives. Although the model's explanatory power is modest, the empirical evidence helps clarify how digital depth, innovation, and performance are interconnected in one of the world's largest manufacturing economies.

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Authors’ Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study’s findings are fully available within the article.

How to cite this article (APA)

Jiang, C., Pimdee, P., & Sukkamart, A. (2026). DIGITAL TRANSFORMATION AND FIRM PERFORMANCE IN CHINESE MANUFACTURING. *Veredas Do Direito*, *23*(6), e235842. https://doi.org/10.18623/rvd.v23.5842