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ORIGINAL CONTRIBUTION

From Digital Transformation to Perceived Enterprise Value: Absorptive Capacity and the Competitive Environment in Chinese Manufacturing

Luchen Leng[1], Khunanan Sukpasjaroen[2]*, Aroonroj Boonkrong[3], Rerkchai Fooprateepsiri[4]

[1,2,3,4]Chakrabongse Bhuvanarth International College of Interdisciplinary Studies, Rajamangala University of Technology Tawan-ok, Bangkok, 10400, Thailand

Abstract— Digital transformation has become increasingly important for manufacturing firms, yet technology investment does not necessarily translate into higher enterprise value. This study examines how digital transformation and external competitive conditions jointly relate to perceived enterprise value and whether absorptive capacity serves as a common organizational mechanism linking these internal and external drivers to value creation. A survey was conducted among Chinese manufacturing enterprises. Using a key-informant sampling approach, one eligible employee or manager with knowledge of the firm's digital initiatives, competitive environment, organizational learning, and performance was selected from each enterprise. After data screening, 400 valid responses were retained and analyzed using Covariance-Based Structural Equation Modeling (CB-SEM) and 5,000-sample bias-corrected bootstrapping. The results show that digital transformation (β = .18) and Diamond Model factors (β = .21) are positively associated with perceived enterprise value, while both exhibit stronger associations with absorptive capacity (β = .43 and β = .39, respectively). Absorptive capacity has the strongest direct association with perceived enterprise value (β = .40) and significantly mediates the relationships between digital transformation and perceived enterprise value (indirect effect = .172, 95% CI [.111, .244]) and between Diamond Model factors and perceived enterprise value (indirect effect = .156, 95% CI [.101, .220]). The study's originality lies in integrating firm-level digital transformation and Diamond Model conditions within a single dual-driver framework and identifying absorptive capacity as a shared knowledge-conversion mechanism through which internal digital resources and external competitive conditions are associated with enterprise value. The findings suggest that firms should complement digital investment with organizational learning and knowledge-application capabilities. However, the cross-sectional, single-informant, self-reported design limits causal inference and generalizability. Future research should employ longitudinal and multi-informant designs, incorporate objective financial indicators, and examine the model across industries, regions, and national contexts.

Index Terms— Digital transformation, Prceived enterprise value, Absorptive capacity, Diamond Model, Manufacturing, China.

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Introduction

Digitalisation has gradually moved from being an optional technological advancement to becoming the core reform of how enterprises generate value in production, coordination, learning, and innovation. Digital technology has changed the scope of organisations, the pattern of information transmission, customer interactions, supply chain networks, and business models; thus, its effects are no longer confined to the application of software or automated machinery (Bharadwaj et al., 2013; Matt et al., 2015; Vial, 2021). Manufacturing has a higher demand for this change

*Corresponding Author: khunanan_su@rmutto.ac.th

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because information technology needs to be combined with operational technology, production facilities, engineering knowledge, supplier networks, and quality control processes. Changes in the capital intensity and interdependence of these factors make manufacturing a difficult case for studying whether digital transformation increases long-term enterprise value.

Evidence from China increasingly links digitalisation with enterprise value, innovation, growth, financial performance, and capital-market quality. Digitalisation can enhance the value of listed Chinese manufacturing enterprises through dual-direction innovation (Ma et al., 2022), increase the value of metal enterprises (Zhang et al., 2023), strengthen the quality of innovation (Zhao et al., 2025), and support enterprise development under different financing conditions (M. Li & Wei, 2024). Related studies have found that digital investment can promote increase in enterprise value through intellectual capital (Bai et al., 2024), and financial digital transformation enhances performance by strengthening information symmetry and reducing operating costs (Liu et al., 2023). Digital technology can also increase the liquidity and development of capital markets (Liu et al., 2023). Together, these results show that digitalisation has had some economic effects, but they do not indicate that investment in digitalisation has been converted into value.

The main problem is how to achieve this conversion. Digital projects generally have high short-term adjustment costs, disrupt existing routines, and generate data that cannot be used immediately by the organisation. Although the company has purchased high-end platforms, it does not have the necessary skills, coordinated processes, and knowledge-processing capabilities to use them effectively. Digitalisation is thus a type of capacity building rather than a technology-purchase decision (Warner & Wäger, 2019). According to the theory of dynamic capabilities, continuous high performance is achieved by adapting to changes, taking advantage of opportunities, and reallocating resources; it is not based solely on having resources (Teece, 2018). The reason for the different outcomes of the same investment is as follows.

The above research has only focused on the internal path to innovation, such as intellectual property and reduced costs. The above mechanisms are necessary but not sufficient due to the nature of industrial systems. Access to digital talents and facilities, high-end demand, specialised suppliers, government support, and competition all affect the availability of knowledge and firms' willingness to use it. Porter (1990) Diamond Model offers a system of explanation for these environmental conditions. Later studies have applied the model to Chinese electronics, engineering services, cross-border e-commerce, renewable energy, and regional competitiveness, among other areas, showing that it can be used in other countries as well (Fang et al., 2018; Rashidin et al., 2020; Yang et al., 2024; Zhao et al., 2025).

The literature consequently leaves three connected gaps. First, most studies on the impact of digitalisation on enterprise value are still direct-effect models, although recent evidence repeatedly indicates intervening organisational capabilities. Second, most studies using the Diamond Model only assess overall competitiveness and do not incorporate environmental factors into firm-level value-creation models. Third, internal digital resources and external competitive conditions are rarely connected by a common organisational system. Absorptive capacity is a system of routines that firms use to discover, absorb, adapt, and apply external knowledge (Cohen & Levinthal, 1990; Zahra & George, 2002) in the face of such deficiencies. It can organise digital information and ecosystem resources to promote process optimisation, innovation, high-quality cash flow, and sustainable development.

This study responds by constructing and testing an integrated Digital Transformation-Diamond Model-Absorptive Capacity-Perceived Enterprise Value framework in Chinese manufacturing. Digitalisation is regarded as the internal driver, the factors of the Diamond Model as the external driver, absorptive capacity as the value-conversion mechanism, and perceived enterprise value as a multi-dimensional perceptual outcome consisting of free cash flow, profitability, and sustainable development ability. The two problems of this paper are: Are internal digitalisation and external competition independently related to a company's value? To what extent are these associations transmitted by absorptive capacity?

The three research contents are: In theory, this study integrates the resource-based view, national competitive advantage theory, dynamic capabilities, and absorptive capacity to build an economic dual-driver model. Based on survey data from 400 respondents in all manufacturing sectors and firm sizes, it concurrently estimates the direct and indirect effects empirically. In practice, it distinguishes between digital investment and capability construction, and thus needs to develop knowledge systems and industrial ecosystems in tandem with technological infrastructure. Therefore, the focus of this paper will be on how internal changes and external factors affect a company's perceived value, rather than whether digitalisation is related to value creation.

Literature Review and Hypothesis Development

Theoretical foundations

The resource-based view attributes performance differences to valuable, rare, inimitable, and organisationally embedded resources (Barney, 1991; Wernerfelt, 1984). Hardware and software alone rarely meet these demands for digitalisation because competitors have also obtained similar technologies. Frims can use digital resources in conjunction with its own data, domain knowledge, routines, culture, and management coordination. Bharadwaj et al. (2013) thus conceptualize digital strategy as the integration of business and information-technology strategy, and Vial (2021) defines digital transformation as an organisational response to technology-induced disruption that alters value-creation paths. Therefore, the resource-based view supports the idea of internal digital resources but needs to explain how these resources are used productively through capabilities.

Dynamic-capabilities theory offers an explanation. Teece (2018) believes that a company undergoing changes should promptly recognise new

opportunities and risks, then make reasonable investments and choices, and reallocate its resources. Digitalisation is a continuous process of strategic renewal that requires repeated reconfiguration rather than a one-time implementation (Warner & Wäger, 2019). Verhoef et al. (2021) have further divided digitisation, digitalization, and believe that transformation also includes organisational structure, and business model. Kraus et al. (2022), as well as Hanelt et al. (2021), have also referred to digitalisation as multi-level organisational change. These accounts believe that value is achieved through complementary organisational capabilities rather than by technological intensity alone.

The Theory of comparative advantage is externally focused. Porter (1990) Diamond Model attributes competitiveness to the system of factor conditions, demand conditions, related and supporting industries, firm strategy, structure, and rivalry, and is shaped by government and chance. Later extensions have shown that multinational activities and international connections can expand the relevant diamond (Moon et al., 1998; Rugman & D'cruz, 1993). Factor conditions in the digital age include broadband and industrial data infrastructure, financing, digital talent, demand conditions such as sophisticated customers and rapid feedback, supporting industries such as cloud, software, logistics, and specialised suppliers, and accelerated rivalry through experimentation. Government regulations, standards, subsidies, and other factors also affect the incentives for and access to knowledge.

Absorptive capacity relates the two internally and externally. Cohen and Levinthal (1990) were the first to propose that a company's absorptive capacity refers to its ability to recognise the value of new external knowledge, absorb it, and apply it commercially. Zahra and George (2002) later distinguished between potential absorptive capacity—acquisition and assimilation—and realised absorptive capacity—transformation and exploitation. Lane et al. (2006) proposed that the construct should be connected to actual organisational learning, and Todorova and Durisin (2007) have shown that knowledge transformation has recursive and path-dependent characteristics. At present, the model does not use the term general ability. It is the set of procedures for turning digital information and environmental opportunities into operating and strategic results.

Together, these theories propose a sequence. Digitalisation expands the firm's internal capacity for information collection and processing. Diamond Model factors determine the quality and quantity of external knowledge, resources, and competitive signals. Absorptive capacity determines whether the input is absorbed, recognised, recombined, and used. Perceived enterprise value is the resulting assessment of cash-flow quality, profitability, and long-term development capacity. The resulting framework does not present either technological determinism or environmental determinism; firms require agency and capabilities, but these capabilities develop and operate in an ecosystem.

Digital transformation and perceived enterprise value

Digitalisation will alter the value of the company in several ways. Integrated data and automation can reduce coordination costs, shorten the production cycle, improve quality, and increase asset utilisation. Customer analysis and related products can expand the scale of sales, and digital supply chains will reduce inventory and improve flexibility. Digital reporting can improve information symmetry and capital allocation. Liu et al. (2023) found that information symmetry and operating costs mediate the effect of financial digitalisation on financial performance. Liu et al. (2023) connect digital technology with firm and capital-market quality through liquidity, and show that value creation also occurs in an improved external information environment.

The other is innovation. Ma et al. (2022) found that digitalisation increases the value of listed Chinese manufacturing enterprises through technological innovation, business model innovation, and their combination. Zhao et al. (2025) also show that digitalisation enhances the quality of innovation. ZZhang et al. (2023) found that digitalisation positively affects the value of Chinese metal enterprises, and M. Li and Wei (2024) have also linked digitalisation to enterprise expansion and identified financing constraints as a prerequisite. Digital investment can also increase the value of the company by building human, structural, and relational capital (Bai et al., 2024). Together, the above studies have shown that technology adds value by constructing organisational and knowledge assets.

A positive correlation does not imply causation. Transformation has adjustment costs, legacy-system conflicts, employee resistance, and cybersecurity risks. Early investments will reduce current profits before learning and scale effects are realised. Thus, the digital-transformation paradox refers to the existence of high strategic intention and uneven implementation results (Vial, 2021). Digitalisation does not mean that there is no benefit; rather, the extent of its application and supporting facilities will determine the extent of its benefits. Transformation combines technology, organisational culture and business processes to expand the expected scale, stability, and sustainability of future cash flows.

Perceived Enterprise Value (PEV) in this study is used as a perceptual multi-dimensional indicator rather than a formula for market capitalisation. The three components are free cash flow, corporate profitability, and sustainable development ability. Based on the economic logic that value is determined by future operating cash flows and risk (Damodaran, 2012), organisations' respondents can assess the creation of operating value without market data. Research on the balanced scorecard also supports all-round performance assessment of enterprises with numerous intangible assets and forward-looking abilities (Kaplan & Norton, 1992; Kaplan & Norton, 1996)). Therefore:

H1. Digital transformation is positively associated with perceived enterprise value.

Diamond Model factors and perceived enterprise value

Porter's Diamond Theory can explain why enterprises in different environments have different degrees of competition despite having similar internal resources. High-end demand promotes quality and innovation; strong suppliers specialise and cooperate in development; factor conditions

affect access to talent, infrastructure, and capital, and competition drives continuous improvement. The government and nature change these relationships by setting standards, providing infrastructure and markets, or causing shocks. The above reasons are not independent; they form a system (Porter, 1990).

Based on the above, this logic is flexible. Zhao et al. (2025) applied the Diamond Model to explore the competitiveness and strategy of foreign architectural and engineering design enterprises in China. Rashidin et al. (2020) examined the competitiveness of Chinese electronics multinational enterprises and found that industry and institutional factors were still relatively prominent. Fang et al. (2018) have adapted the model to assess the competitiveness of renewable energy at the G20 level, and Yang et al. (2024) have evaluated regional competitiveness in China's cross-border e-commerce sector. Although the scope and industries of these studies vary, they all show that competitiveness is the result of an all-round combination of resources, markets, industrial support, and governance.

The above conditions directly affect the opportunities and constraints for value creation in manufacturing enterprises undergoing digitalisation. Digital infrastructure and skilled labour reduce implementation costs. High-end customers return new products and services more often. Strong software, logistics, equipment, and platform suppliers improve interoperability and reduce the development cycle. Predictable Government Policies Reduce Uncertainty; Rivalry Inhibits Symbolic Adoption. On the other hand, fragmented standards, weak suppliers, a shortage of talent, and unstable regulations can reduce value despite substantial investments by the company. Therefore, the conditions of the Diamond Model may act as an external driver of perceived enterprise value rather than just a descriptive background.

H2. Diamond Model factors are positively associated with perceived enterprise value.

Digital transformation and absorptive capacity

Digitalisation can enhance absorption capacity by expanding the scope of accessible knowledge and building an organisational system for processing this knowledge. Digital Platforms collect signals from customers, suppliers, equipment, and the market. A shared database and analysis platform can increase the visibility of departmental knowledge. Process digitisation codifies routines and enables traceable experiments. The above mechanisms help to acquire, process, apply, and use knowledge.

The Effect of Ability is Organisational Integration. Digital systems that remain isolated in the technical department will increase information overload without improving learning. Therefore, organisational culture change and cross-functional process redesign are also parts of digitalisation. Warner and Wäger (2019) define digital transformation as strategic renewal through capabilities, and Liu et al. (2023) show that the competence requirements for managers have been altered in the digital era to include technical, managerial, and relational abilities. Recently, some studies have connected digital capability with innovation performance via absorptive capacity (Kastelli et al., 2024). SMEs' cases also show that digitalisation is promoting innovation and expanding markets to drive growth (Kobusingye et al., 2026).

The Foundation is also cumulative. Digital investments generate richer information and frequent external connections; repeated use builds routines for screening, interpreting, and applying knowledge, and these routines increase the returns of subsequent digital investments. Therefore, the above recursive process is in line with the path-dependence theory proposed by Cohen and Levinthal (1990).

H3. Digital transformation is positively associated with absorptive capacity.

Diamond Model factors and absorptive capacity

The External Competitive Environment also affects the development of absorptive capacity. The high demands of the enterprise provide rich learning material. A dense network of suppliers and service providers offers channels for knowledge sharing and joint-problem-solving. Competition increases the demand for interpreting market and technology signals. Factor conditions determine whether firms can hire people with the ability to assimilate specialised knowledge, and stable public policies and technical standards reduce uncertainty in collaborative learning.

Studies of the Diamond Model often consider these factors to be predictors of competitiveness and have also provided some insights. Regional differences in Chinese cross-border e-commerce are due to variations in digital infrastructure, research investment, market size, and enterprise ecosystems (Yang et al., 2024). Revised Diamond Model research similarly shows that regulatory, industrial, resource, and market conditions jointly determine renewable-energy competitiveness (Fang et al., 2018). The environment of the firm will affect the supply, diversity, and applicability of external knowledge. Therefore, a strong ecosystem is expected to be positively correlated with the perceived value of a company due to its learning capabilities.

H4. Diamond Model factors are positively associated with absorptive capacity.

Absorptive capacity and perceived enterprise value

Absorptive capacity adds value by fully utilizing knowledge that has little economic benefits when not applied. Acquisition helps the company learn new technologies and market information; assimilation forms a common language; transformation combines the new knowledge with existing routines; and exploitation applies this knowledge to produce products, processes, and business decisions (Zahra & George, 2002). The above activities will accelerate the pace of innovation and improve production quality.

Absorptive capacity can help to solve the problem of exploration and exploitation. The company needs new ideas to expand its resource base and should integrate these ideas with existing production knowledge. High-absorption-capacity material will reduce the cost and uncertainty of this integration. Thus, it will increase profitability and free cash flow and strengthen long-term development ability. In line with dynamic-capabilities theory, the organisation will continuously be renewed in response to changes in the environment (Teece, 2018), and empirical studies have shown that capability development mediates the impact of digitalisation on performance.

With the changes in technology and the diversity of regional ecosystems, China's manufacturing industry is moving from cost-based competition to innovation-driven development, and this system is very suitable for it. Digital technology provides more opportunities, but the country's absorptive capacity will determine how well these opportunities can be realised economically.

H5. Absorptive capacity is positiv,ely associated with perceived enterprise value.

The mediating role of absorptive capacity

The above arguments suggest two mediated paths. Firstly, digitalisation will improve the accessibility and coordination of data; value will be added through learning from this resource and applying that learning in operations. The logic is consistent with the findings that ambidextrous innovation mediates the value effect of digitalisation (Ma et al., 2022), intellectual capital mediates the effect of digital investment (Bai et al., 2024), and information symmetry and operating cost transmit the effects of financial digitalisation (Liu et al., 2023). Generally speaking, it refers to a company's capability for knowledge absorption, integration, and application.

Second, although the factors in the Diamond Model provide opportunities, pressures, and knowledge flows, different firms have different degrees of utilisation. Favourable demand, infrastructure, suppliers, and policies cannot guarantee value if the focal firm lacks learning routines. A high-absorption-capacity firm will be able to obtain more benefits from the external ecosystem. The mediation path extends the national competitive advantage theory by showing how the firm is affected by the environment and thus economically disadvantaged.

Together, the two paths constitute a dual-driver system. Digitalisation provides the internal information-processing and reconfiguration resources; the Diamond Model offers external knowledge and competitive stimuli; and absorptive capacity converts both into perceived enterprise value. The framework puts forward partial mediation because digitalisation and the environment can also connect to value via paths that do not fall under absorptive capacity, such as automation, financing, market access, and direct cost reduction.

H6. Absorptive capacity mediates the positive association between digital transformation and perceived enterprise value.

H7. Absorptive capacity mediates the positive association between Diamond Model factors and perceived enterprise value.

Integrated model and expected contribution

The three differences between the new and old models are as follows. First, it puts two analytically different drivers in the same model. Digitalisation reflects choices and rearrangements within the company, while the factors in the Diamond Model are the opportunities for the company. Simultaneously estimating both sets of drivers reduces the risk of attributing external advantages to the firm's internal digital capabilities or treating firm-specific transformation as an unexplained outcome of the environment.

Second, the model takes absorptive capacity as a general conversion factor. Instead of proposing separate mediators for each antecedent, this specification is relatively loose and assumes that both digital resources and ecosystem conditions are transmitted through the same organisational routines. The company applies the same acquisition, interpretation, transformation, and exploitation processes to learn from digitally generated data, customer feedback, suppliers, competitors, universities, and policy signals. If available, this common-mechanism argument can offer a parsimonious explanation for why several different value pathways—innovation, intellectual capital, information symmetry, cost reduction, and market expansion—frequently appear in digital-transformation research. The above results can be viewed as expressions of a deeper knowledge-conversion ability.

Third, the system links ability development with all kinds of values. Research on profitability alone may fail to consider the transformation benefits of resilience, learning, and sustainable development; research focused only on innovation may lack financial relevance. Free cash flow is the internal financing effect of operations; profitability reflects economic efficiency; and the capacity for development shows the long-term performance of the company. Recent Chinese studies have shown that digitalisation can enhance ESG performance through improved absorptive capacity, thus adding support to the long-term dimension (W. Li & Zhang, 2024).

The model does not present an interaction between digitalisation and the Diamond Model because the analysis estimates only additive direct and indirect paths. Conceptually, interaction is feasible; support ecosystems can increase the returns to digitalisation, and high-end digital capabilities can enhance the utilisation of ecosystem resources. Testing such complementarity would require a product term, a multigroup comparison, or latent moderated structural equation that is outside the current model. Therefore, the study puts forward a more restricted claim that internal and external drivers are simultaneously, independently, and capability-mediatedly associated with perceived enterprise value.

Model fit was selected as the evaluation standard and not as a substantive hypothesis. Fit indices indicate how well the given covariance structure fits the actual data but do not show a direction of theoretical change. Figure 1 is the proposed path.

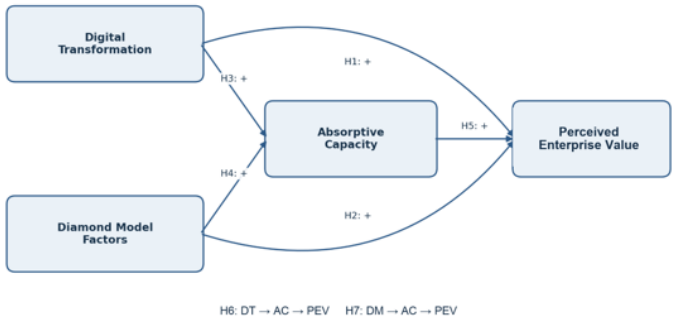

Fig. 1 *Proposed conceptual model*

Method

Research design and sample

The design is a cross-sectional study. The participants of this study are employees and managers of Chinese manufacturing enterprises who are aware of the company's digital initiatives, the external competitive environment, the learning process and performance. Manufacturing is chosen because the digitalisation of this industry requires the integration of information technology with equipment, production processes, engineering knowledge, organisational structure, and supply chain.

The dataset in this paper was provided by the first author as part of the research foundation for this study. The survey was designed and conducted for the present research programme, and the first author is responsible for the original data collection and analysis. The present manuscript reports the measurements and structural analyses performed on this original dataset. The sampling frame contained 1,321 eligible manufacturing enterprises. A single key informant was selected per enterprise to avoid within-firm bias in the observations. Informants held positions in digital transformation, information systems, strategy, operations, or other management positions.

Participation was voluntary, and the subjects were informed of the purpose of the study, approximate time, anonymity, and confidentiality. Questionnaires were distributed electronically to the organisational contacts, and reminders were sent to non-respondents. The unity of analysis is the respondent's evaluation of the enterprise, and one designated informant is used per enterprise. The self-reported indicators reflect the perception of the organisational environment and enterprise value, not audited firm-level financial data.

Table I
Sample profile

Variable	Category	*n*	%
Gender Gender	Female	195	48.75
	Male	205	51.25
Education	Below bachelor's	21	5.25
	Bachelor's	227	56.75
	Master's	138	34.50
	Doctoral	14	3.50
Experience	< 1 year	20	5.00
	1–3 years	74	18.50
	4–6 years	74	18.50
	7–10 years	91	22.75
	> 10 years	141	35.25
Industry	Electronic equipment	90	22.50
	Mechanical products	87	21.75
	Medicine/chemical	104	26.00
	Other manufacturing	119	29.75
Employees	20–300	209	52.25
	300–1,000	154	38.50
	> 1,000	37	9.25

Note. *N* = 400. Percentages are based on the final analytic sample.

Based on the above research, some indicators were selected to form a preliminary set of items for the questionnaire. Five experts were consulted to improve the clarity and applicability of the items. All the constructed items are five-point Likert scales, with 1 indicating "strongly disagree"

and 5 indicating ”strongly agree”. There are 52 index items and 8 demographic items in total. Table II shows the construct operationalisations.

The 12 indicators of digitalisation are technology, changes in organisational culture, business processes, and customer experience. As shown in the above dimensions, digitalisation is changing the organisation’s structure, and value creation mechanism rather than just modifying technical facilities (Matt et al., 2015; Verhoef et al., 2021; Vial, 2021). The 18 items of the Diamond Model factors included a firm’s strategy, structure and rivalry; demand conditions; factor conditions; related and supporting industries; government; and chance (Porter, 1990). The addition of government and chance follows the general applied Diamond Model.

According to Zahra and George (2002), the 12 indicators of acquisition, assimilation, transformation, and exploitation were used to measure absorptive capacity. The item-level measurement analysis retained all four dimensions after comparing the four-factor model with the three-factor model that combined acquisition and assimilation, and the same 12 items were kept. Assimilation had the lowest higher-order loading (β = .55), but the four-dimensional model met the conventional fit, reliability, and convergent validity criteria and provided better theoretical support. The ten perception indicators for the perceived enterprise value included free cash flow, corporate profitability, and sustainable development ability. The construct is therefore labeled perceived enterprise value and does not represent an accounting identity or market valuation.

The mode of measurement should be in line with the purpose of explanation and interpreted reasonably. Perceived enterprise value can reflect private-firm and operational results not immediately reflected in market prices, but it cannot replace audited cash flow or Tobin’s Q data. Therefore, this paper will investigate the impact of organisation perception and identify objective financial indicators for subsequent research.

Table II
Construct operationalization

Construct	Dimensions	Items	Conceptual sources
Digital transformation	Technology; culture transformation; business process; customer experience	12	Vial (2021); Verhoef et al. (2021)
Diamond Model factors	Strategy/structure/rivalry; demand; factors; supporting industries; government; chance	18	Porter (1990); Fang et al. (2018)
Absorptive capacity	Acquisition; assimilation; transformation; exploitation (initial instrument)	12	Cohen & Levinthal (1990); (Zahra & George, 2002)
Perceived enterprise value	Free cash flow; profitability; sustainable development capability	10	Damodaran (2012); Kaplan & Norton (1992)

Note. All construct items were rated on five-point agreement scales. The revised measurement model retained acquisition, assimilation, transformation, and exploitation as the four dimensions of absorptive capacity.

Data analysis

Analysis proceeded in seven stages. First, data screening examined item-level missingness, duplicate records, impossible values, and long-string response patterns. Twenty-one questionnaires that did not meet the prespecified screening criteria were excluded before analysis. No retained respondent had more than 5% missing construct items, and item-level missingness was below 1%. Descriptive statistics were calculated using available item responses, and no mean substitution was used. Confirmatory factor analysis and structural equation modeling used Full-Information Maximum Likelihood (FIML), allowing all 400 retained cases to contribute to model estimation. Item direction was standardized so that higher scores represented stronger levels of each construct. Second, frequencies, means, standard deviations, skewness, and kurtosis described the sample and observed dimensions. Third, internal consistency was assessed using item-level corrected item-total correlations and dimension-level Cronbach’s alpha. Fourth, exploratory factor analysis evaluated dimensionality, with sampling adequacy assessed through the Kaiser-Meyer-Olkin statistic and Bartlett’s test of sphericity. Fifth, confirmatory factor analysis evaluated standardized loadings, Composite Reliability (CR), Average Variance Extracted (AVE), latent correlations, the Fornell-Larcker criterion, and Heterotrait-Monotrait Ratios (HTMT). Alternative one-, two-, three-, and four-construct measurement models and competing absorptive-capacity specifications were compared.

Sixth, common method variance was assessed using Harman’s single-factor test on the 52 original items, a single-factor CFA using the same 17 first-order dimension indicators as the measurement model, and a common latent factor sensitivity analysis. In the common latent factor model, each observed dimension loaded on both its substantive higher-order construct and a common method factor. The common method factor was constrained to be orthogonal to the substantive constructs, and its variance was fixed to one for identification. Structural coefficients from the baseline and common-latent-factor models were compared to assess sensitivity to shared method variance.

Seventh, covariance-based SEM estimated the five hypothesized direct paths while allowing digital transformation and Diamond Model factors to covary. The hypothesized partial-mediation model estimated all six pairwise relations among the four latent constructs and was therefore saturated at the construct level. Its global fit was likelihood-equivalent to that of the four-construct measurement model. Structural inference consequently relied on individual parameter estimates, 5,000-sample bias-corrected bootstrap confidence intervals for indirect associations, and comparisons with theoretically restricted nested models. Model reporting used χ^2, degrees of freedom, χ^2/df, CFI, TLI, RMSEA, SRMR, and Hoelter critical N at the .05 and .01 levels. Direct paths were reported with unstandardized estimates, standard errors, critical ratios, *p* values, confidence intervals, and standardized coefficients.

Results

Sample characteristics, data screening, and descriptive statistics

The 400 respondents represented a balanced gender distribution and heterogeneous organizational backgrounds (Table I). More than one third had over ten years of work experience. A total of 52.25% represented firms with 20–300 employees, and 38.5% represented firms with 300–1,000 employees. The sector distribution included electronic equipment, mechanical products, medicine and chemicals, and other manufacturing. This variation supports examination of the model across a broad manufacturing context, although the data are not statistically representative of every Chinese manufacturing subsector.

Observed-dimension means remained tightly clustered between 3.182 and 3.207, indicating moderate assessments across digital transformation, Diamond Model conditions, absorptive capacity, and perceived enterprise value. Item-level means ranged from 2.95 to 3.42, and item-level standard deviations ranged from .76 to 1.05. Overall item missingness was .38%, no item exceeded .75% missingness, and all 400 retained cases contributed to CFA and SEM estimation through FIML. Among the retained cases, screening identified no material duplicate, impossible-value, or long-string response problem. Technology recorded the highest digital-transformation mean (M = 3.207, SD = .892), whereas organizational culture transformation was lowest (M = 3.182, SD = .876). Across the remaining constructs, the moderate means were similarly concentrated, without severe floor or ceiling effects. Complete descriptive and item-analysis statistics for all 52 items are reported in Supplementary Table S1.

Dimension-level Cronbach's alpha values ranged from .74 to .88. Item-level corrected item-total correlations are reported in Supplementary Table S1 rather than being summarized as a single ambiguous dimension statistic. The alpha coefficients and corrected item-total correlations support internal consistency while showing meaningful variation across the 17 first-order dimensions. Table III reports the dimension-level results.

Table III
Normative mapping of empirically identified schemes and supplementary legal risk categories in public procurement

Construct	Dimension M	SD	Skew.	Kurt.	*α*
DT	Business process 3.188	0.902	-.12	-.20	.82
DT	Customer experience 3.197	0.893	.09	-.11	.80
DT	Culture transformation 3.182	0.876	.18	-.37	.78
DT	Technology 3.207	0.892	-.22	-.06	.84
DM	Chance 3.198	0.879	.05	-.14	.76
DM	Demand conditions 3.198	0.886	-.10	.03	.81
DM	Factor conditions 3.193	0.898	.08	-.29	.83
DM	Strategy/structure/rivalry 3.199	0.894	-.14	.12	.85
DM	Government 3.188	0.886	.16	-.34	.79
DM	Related/supporting industries 3.197	0.902	-.03	.19	.82
AC	Acquisition 3.202	0.887	-.12	.05	.81
AC	Assimilation 3.201	0.891	.08	-.22	.74
AC	Exploitation 3.187	0.883	.13	-.31	.88
AC	Transformation 3.202	0.882	-.09	.36	.86
PEV	Free cash flow 3.198	0.900	-.04	-.14	.83
PEV	Profitability 3.187	0.896	.11	-.28	.85
PEV	Sustainable development 3.193	0.891	-.07	.10	.84

Note. DT = digital transformation; DM = Diamond Model factors; AC = absorptive capacity; PEV = perceived enterprise value. Alpha values are reported at the dimension level; item-level corrected item-total correlations are reported in Supplementary Table S1.

Measurement model and convergent validity

The Kaiser-Meyer-Olkin statistic was .921, and Bartlett's test of sphericity was significant, $\chi^2(136) = 2{,}827.323$, $p < .001$. The correlation matrix was therefore suitable for factor analysis. The rotated solution identified four higher-order groupings corresponding to the focal constructs. Rotated loadings ranged from .406 to .761, with most dimensions exceeding .50. Assimilation had the lowest exploratory loading (.406), so its status was examined through an item-level comparison of the four-factor model and a three-factor model that combined acquisition and assimilation while retaining the same 12 items.

The four-construct measurement model showed acceptable fit, $\chi^2(113) = 183.10$, $p < .001$, $\chi^2/df = 1.62$, CFI = .966, TLI = .959, RMSEA = .039, and SRMR = .041. These indices indicate good but not exact fit and do not require interpretation of a TLI above 1 or an RMSEA truncated at zero. The model used the 17 first-order dimensions as indicators of the four higher-order constructs; it did not use item parcels created after inspection of modification indices.

Digital-transformation dimension loadings ranged from .622 to .778; Diamond Model dimension loadings ranged from .674 to .797; absorptive-capacity loadings ranged from .550 to .819 across acquisition, assimilation, transformation, and exploitation; and perceived-enterprise-value

loadings ranged from .697 to .735. CR ranged from .757 to .867, and AVE ranged from .505 to .522, supporting internal consistency and convergent validity at the higher-order construct level (Table IV). Complete CFA and SEM reporting output is provided in Supplementary Section S2.

Table IV
Standardized measurement loadings, composite reliability, and average variance extracted

Construct	First-order dimension	Loading	CR	AVE
DT	Technology	.778	.802	.505
	Culture transformation	.760		
	Business process	.622		
	Customer experience	.670		
DM	Strategy/structure/rivalry	.797	.867	.522
	Demand conditions	.674		
	Factor conditions	.741		
	Related/supporting industries	.734		
	Government	.700		
	Chance	.682		
AC	Acquisition	.701	.802	.508
	Assimilation	.550		
	Transformation	.754		
	Exploitation	.819		
PEV	Free cash flow	.710	.757	.510
	Profitability	.735		
	Sustainable development	.697		

Note. The four-dimensional AC specification retained assimilation. CR = composite reliability; AVE = average variance extracted.

Discriminant validity and alternative measurement models

The square roots of AVE exceeded the corresponding latent correlations, and all HTMT ratios were below .85 (Table V). The DT-DM correlation was .320; the remaining latent correlations ranged from .469 to .611, and the maximum HTMT ratio was .75. These results support empirical separation of the four focal constructs; complete discriminant-validity output is provided in Supplementary Section S2.

Table V
Latent correlations, square roots of AVE, and HTMT ratios

Construct	DT	DM	AC	PEV
DT	.710	.42	.67	.58
DM	.320	.723	.64	.60
AC	.555	.528	.713	.75
PEV	.469	.479	.611	.714

Note. Bold diagonal entries are square roots of AVE; values below the diagonal are latent correlations; values above the diagonal are HTMT ratios. DT = digital transformation; DM = Diamond Model factors; AC = absorptive capacity; PEV = perceived enterprise value.

Competing models fitted progressively worse as the four focal constructs were collapsed (Table VI, Panel A). The one-factor model showed poor fit, while the proposed four-construct model showed the strongest fit. Using the same 12 absorptive-capacity items, an item-level nested comparison also favored the theoretically complete four-factor model over a three-factor model in which acquisition and assimilation were combined (Panel B).

Table VI
Alternative measurement and absorptive-capacity models

Model	χ^2(df)	χ^2/df	CFI	TLI	RMSEA	SRMR	Comparison
Panel A: Focal-construct measurement models							
Four-construct model	183.10 (113)	1.62	.966	.959	.039	.041	Proposed
Three-factor model	317.80 (116)	2.74	.902	.885	.066	—	AC+PEV merged
Two-factor model	426.00 (118)	3.61	.851	.828	.081	—	DT+DM; AC+PEV
One-factor model	606.90 (119)	5.10	.763	.730	.101	.095	All merged
Panel B: Item-level AC models							
Four-factor AC	71.60 (48)	1.49	.976	.967	.035	.036	Four dimensions
Three-factor AC	112.40 (51)	2.20	.939	.921	.055	.060	ACQ+ASM merged

Note. Panel A compares the proposed four-construct measurement model with models that collapse conceptually adjacent constructs. Panel B compares absorptive-capacity models using the same 12 items; the three-factor model combines acquisition and assimilation. A dash indicates that an SRMR value was not reported for that comparison.

Absorptive-capacity specification

The four-dimensional absorptive-capacity model provided significantly better fit than the three-factor model in which acquisition and assimilation were combined, $\Delta\chi^2(3) = 40.80$, $p < .001$. Although assimilation had the weakest higher-order loading ($\beta = .55$), the four-dimensional model met overall fit, composite reliability, and average variance extracted criteria. Assimilation was therefore retained on the combined basis of theoretical specification and empirical model comparison rather than deleted solely because it had the weakest exploratory loading. Reestimating the original three-dimensional model with assimilation omitted changed the structural coefficients by no more than .02 (Supplementary Section S3).

Common method variance assessment

The first unrotated factor in Harman's test of the 52 original items accounted for 31.4% of total variance. Using the same 17 first-order dimension indicators as the four-construct measurement model, the one-factor CFA showed poor fit, $\chi^2(119) = 606.90$, $p < .001$, $\chi^2/df = 5.10$, CFI = .763, TLI = .730, RMSEA = .101, and SRMR = .095. The same-indicator comparison therefore showed that the covariance pattern was not fully attributable to a single common method source (Supplementary Section S4).

The common latent factor sensitivity analysis reduced the five standardized structural coefficients by .02 to .03 without changing their directions or inferential conclusions (Table VII; Supplementary Section S4). Shared method variance may have contributed modestly to coefficient magnitude, but the results were not fully attributable to a single common method source.

Table VII
Common latent factor sensitivity analysis

Path	Baseline β	CLF-adjusted β	Difference
DT → PEV	.18	.16	.02
DM → PEV	.21	.19	.02
DT → AC	.43	.40	.03
DM → AC	.39	.36	.03
AC → PEV	.40	.37	.03

Note. CLF = common latent factor; β = standardized coefficient.

Table VIII
Common latent factor sensitivity analysis

Model	χ^2(df)	*p*	χ^2/df	CFI	TLI	RMSEA	SRMR	Hoelter CN .05/.01
Measurement	183.10 (113)	< .001	1.62	.966	.959	.039	.041	303 / 330
Structural	183.10 (113)	< .001	1.62	.966	.959	.039	.041	303 / 330

Note. CN = Hoelter critical N. Both CN values exceed the commonly referenced benchmark of 200. The structural portion of the hypothesized model is saturated at the construct level; its identical global fit follows from a likelihood-equivalent reparameterization of the four-construct measurement model

Structural model and direct effects

Because the hypothesized partial-mediation specification was saturated at the latent structural level, its global fit was the same as that of the four-construct measurement model (Table VIII). Structural inference therefore focused on the estimated paths and comparisons with theoretically restricted nested models. All five direct paths were statistically significant, but they had different sizes. Digitalisation was positively associated with

the perceived enterprise value (B = .184, SE = .066, CR = 2.79, *p* = .005, *β* = .18), supporting H1. Factors in the Diamond Model were also positively associated with perceived enterprise value (B = .214, SE = .061, CR = 3.51, *p* < .001, *β* = .21), supporting H2. The correlation between digitalisation and the factors of the Diamond Model was 0.32 (*p* < 0.001), indicating a relationship but not identity. Digitalisation was positively associated with the absorptive capacity (B = .447, SE = .057, CR = 7.84, *p* < .001, = .43) and thus supported H3. Factors of the Diamond Model were also positively associated with absorptive capacity (B = .401, SE = .055, CR = 7.29, *p* < .001, *β* = .39), supporting H4. Absorptive capacity was positively associated with perceived enterprise value (B = .395, SE = .057, CR = 6.93, *p* < .001, *β* = .40), and thus supported H5. The antecedent associations with absorptive capacity were larger than their direct associations with perceived enterprise value. Table IX shows the full direct-effect estimates.

The model explained 44.4% of the variation in absorptive capacity and 42.9% of the variation in perceived enterprise value. These values show that the model has good explanatory power and is consistent with correlated antecedents and a shared self-report design. Cross-sectional estimates show the average association in the sample and cannot determine temporal causality. All five direct hypotheses were supported, but the coefficients showed a differentiated pattern rather than uniformly large effects. Comparisons with restricted nested models showed significantly worse fit when both direct antecedent-to-outcome paths were fixed to zero, $\Delta\chi^2(2) = 19.30$, $p < .001$; when the absorptive-capacity-to-outcome path was fixed to zero, $\Delta\chi^2(1) = 35.10$, $p < .001$; or when the covariance between the antecedents was fixed to zero, $\Delta\chi^2(1) = 40.50$, $p < .001$ (Supplementary Table S5.5). Absorptive capacity had the largest direct association with perceived enterprise value, and both antecedents were more strongly associated with absorptive capacity than directly with the outcome. Figure 2 summarizes the structural model.

Table IX
Structural paths and direct effects

H	Path	B	SE	CR	*p*	*β*	Decision
H1	DT → PEV	.184	.066	2.79	.005	.18	Supported
H2	DM → PEV	.214	.061	3.51	< .001	.21	Supported
H3	DT → AC	.447	.057	7.84	< .001	.43	Supported
H4	DM → AC	.401	.055	7.29	< .001	.39	Supported
H5	AC → PEV	.395	.057	6.93	< .001	.40	Supported

Note. B = unstandardized estimate; SE = standard error; CR = critical ratio; *β* = standardized estimate; PEV = perceived enterprise value.

Indirect effects

Table X
Bias-corrected bootstrap indirect effects

H	Indirect pathway	Effect	Boot SE	95% BC CI	Decision
H6	DT → AC → PEV	.172	.034	[.111, .244]	Supported
H7	DM → AC → PEV	.156	.031	[.101, .220]	Supported

Note. BC CI = bias-corrected confidence interval based on 5,000 bootstrap samples. An indirect association is supported when its interval excludes zero.

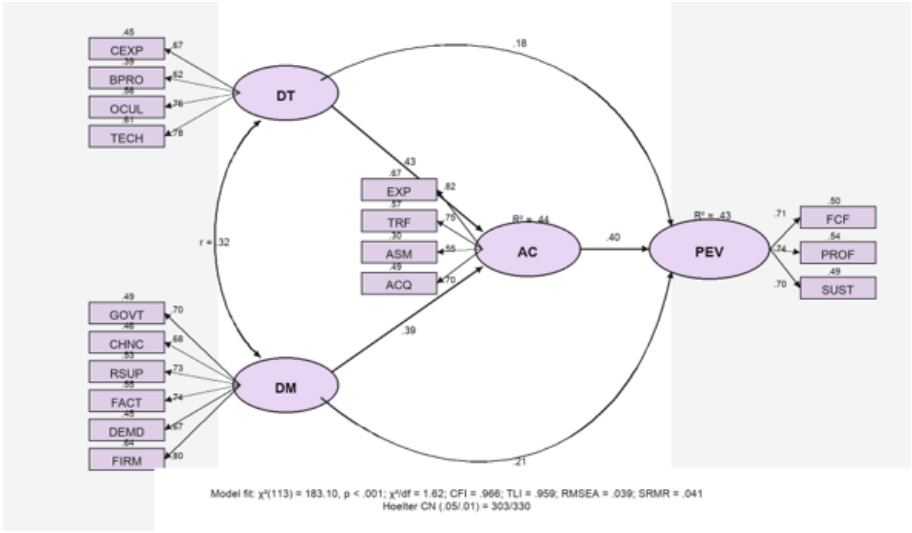

Fig. 2 *Re-estimated structural equation model*

The indirect association of digital transformation with perceived enterprise value through absorptive capacity was .172 (Boot SE = .034, 95% bias-corrected CI [.111, .244]), and the corresponding indirect association for Diamond Model factors was .156 (Boot SE = .031, 95% bias-corrected CI [.101, .220]). Neither interval included zero, supporting H6 and H7 (Table X). The total standardized associations were .352 for digital transformation and .366 for Diamond Model factors, indicating partial statistical mediation.

Discussion

Interpretation of the findings

Digital transformation and Diamond Model conditions were both positively associated with perceived enterprise value, but the principal pattern was not one of uniformly strong direct effects. Their direct associations with perceived enterprise value were modest (β = .18 and .21), whereas their associations with absorptive capacity were stronger (β = .43 and .39). Absorptive capacity showed the largest direct association with perceived enterprise value (β = .40) and accounted for significant indirect associations from both antecedents. Nested-model comparisons further showed that eliminating the direct paths or the absorptive-capacity pathway significantly worsened model fit. The results therefore support a partial capability-conversion account while remaining consistent with the limitations of a cross-sectional, single-informant design.

The positive direct effect of digitalisation on perceived enterprise value is consistent with evidence from several Chinese studies. Ma et al. (2022) connect digitalisation to enterprise value through ambidextrous innovation among listed manufacturers. Zhang et al. (2023) report value creation for metal enterprises, and Zhao et al. (2025) show improvements in innovation quality. M. Li and Wei (2024) argue that digitalisation drives economic growth, but financing problems limit this development. Bai et al. (2024) suggest that intellectual capital is the mediator, and Liu et al. (2023) have found that information asymmetry and operating costs transmit the effect of financial digitalisation. The current results add to these studies by providing a general organisational learning system.

The standardised association between digital transformation and absorptive capacity (.43) was more than double the direct association between digital transformation and perceived enterprise value (.18). This difference has theoretical implications. It indicates that digitalisation is first about what a company can know and do, and only then may these abilities be reflected in perceived value. Integrated information systems increase the frequency, speed, and traceability of knowledge flow; process redesign establishes routines for information application; and digital customer interfaces generate new feedback. However, these resources are only effective if employees and units can interpret and combine them. This pattern is in line with Warner and Wäger (2019) idea of digital transformation as capability-based strategic renewal and the broader dynamic-capabilities argument that reconfiguration mediates the resource-performance relationship (Teece, 2018).

The Diamond Model was positively associated with perceived enterprise value (β = .21) and absorptive capacity (β = .39). Therefore, Diamond Model research has been used to study the value-creation mechanism of organisations rather than national or regional competitiveness. Previous studies have shown that infrastructure, demand, industrial support, strategy, and institutions explain competitiveness in renewable energy, engineering services, electronics, and cross-border e-commerce (Fang et al., 2018; Rashidin et al., 2020; Yang et al., 2024; Zhao et al., 2025). At present, the model indicates that these environmental factors are related to the supply and application of external knowledge. Sophisticated demand generates informative feedback; suppliers and platforms support joint learning; rivalry accelerates search; and government standards reduce coordination ambiguity.

The total standardised association of digital transformation with perceived enterprise value was .352, and the corresponding total association for Diamond Model factors was .366. Their similar magnitudes do not support a simple internal-versus-external ranking. Digitalisation was more closely associated with absorptive capacity, and the Diamond Model had a slightly stronger direct link to perceived enterprise value. Therefore, the higher perceived value is likely the result of changes in the company and improved external competitiveness.

The first is a high-absorptive capacity. Its direct standardised association with perceived enterprise value (.40) was greater than the direct associations of digital transformation and Diamond Model factors. This result is in line with Cohen and Levinthal (1990) view that learning capacity determines the commercial application of external knowledge, and with Zahra and George (2002) division into potential and realised absorptive capacity. Exploitation had the highest higher-order loading (.819), followed by transformation (.754), acquisition (.701) and assimilation (.550). The retained assimilation dimension still has the theoretical distinction between learning knowledge and forming a common understanding of that knowledge.

Bias-corrected bootstrapping supported indirect associations via absorptive capacity. The indirect association of digitalisation was 0.172 (Boot SE = 0.034, 95% CI [0.111, 0.244]), accounting for about 49% of the total association. The indirect association of the Diamond Model factors was 0.156 (Boot SE = 0.031, 95% CI [0.101, 0.220]), accounting for about 43% of the total association. Neither interval included zero; thus, H6 and H7 were supported, and partial mediation occurred in the cross-sectional model.

The results are in line with those reported in other contexts. Kobusingye et al. (2026) have found that innovation and market-expansion capabilities mediate the effect of digitalisation on SME development in East Africa, but technological turbulence may reduce this indirect effect. Cross-context convergence refers to the idea that digitalisation promotes organisational growth through capabilities, and these specific capabilities and environmental structures vary across contexts. The supporting data for a large-scale industrial system in China's manufacturing environment, as well as government policies, regional disparities, and dense manufacturing ecosystems, are all examples of external conditions.

Theoretical implications

The first theoretical contribution is an integrated internal-external model of perceived enterprise value creation. Based on the Resource-Based View and digital-strategy research, firms need firm-specific digital resources, and the Diamond Model introduces various competitive environments. The above views are studied independently. Both are related to absorption capacity, and thus the internal and external drivers enter a single organisational conversion process. The resulting model offers a full explanation of the technology-performance relationship.

Second, the study uses absorptive capacity as the mediating variable for digitalisation and perceived enterprise value. Some previous studies have found that innovation, intellectual capital, information symmetry and operating costs are all mediators (Bai et al., 2024; Liu et al., 2023; Ma et al., 2022). Absorptive capacity is a lower-level, and it explains how firms achieve the above results. A company that can acquire, process, and apply knowledge will be more innovative and create intellectual property; it will reduce information asymmetry and lower costs. Thus, the construct integrates several previous explanations.

Third, the study extends the reasoning of the Diamond Model to firm-level capability development. The Diamond Model is often used as an index or diagnostic tool. Here, the factors predict both perceived enterprise value and absorptive capacity. Thus, the ecosystem can be seen as a repository of knowledge and a pressure-testing training ground for learning, rather than just a location for gains. It can also show how the area and industry of the company affect its own performance.

Fourth, the study clarifies the concept of perceived enterprise value in research on organisational change. Value is shown by free cash flow, profitability, and long-term development ability, rather than a single short-term performance indicator. Given the above reasons, it is expected that the company's operations and future cash flows will be affected by digitalisation. At the same time, the perceptual nature of the measure requires disciplined claims and should motivate future linkage to audited accounting and market data.

Finally, the measurement results support the theory's completeness rather than post-hoc deletion. Although assimilation had the weakest exploratory and confirmatory loadings, the item-level four-factor absorptive-capacity model fitted significantly better than the three-factor model that combined acquisition and assimilation and retained the same 12 items. The four-factor model also achieved CR and AVE requirements. Retention of acquisition, assimilation, transformation and exploitation retains the difference between potential and realised absorptive capacity and makes the weaker assimilation result transparent. The separate model that omitted assimilation produced substantively similar structural estimates (Supplementary Section S3).

Contextual implications for Chinese manufacturing

A typical representative of this model is the manufacturing environment in China. The policy environment for enterprises is favourable, and the development of industrial Internet platforms, intelligent manufacturing, digital supply chains, and technology upgrades is being promoted; however, there are also significant differences in regional infrastructure, skilled labour, finance, supplier networks, and market maturity. A national policy signal will thus lead to very uneven firm-level results. The Diamond Model explains this difference in absorption capacity, and thus firms exposed to the same policies do not react uniformly.

The model is also related to the makeup of the sample. More than half of respondents represented firms employing 20–300 people. These enterprises may have relatively limited resources compared with large-scale production bases and will thus need to employ selective digitalisation and external knowledge sources. Shared industrial platforms, supplier alliances, universities, and public service centres can offset resource deficiencies, but only if the firm has routines for recognising and integrating useful knowledge. The positive association between Diamond Model factors and absorptive capacity is consistent with the above dependence on external ecosystems.

China's manufacturing transformation is also shifting from scale and cost competition to innovation, quality, and high-end, sustainable development. Based on the data from metal enterprises, listed manufacturers, and the capital market, digitalisation has affected production efficiency and innovation quality, as well as enterprise value, information transparency, and liquidity (Liu et al., 2023; Ma et al., 2022; Zhang et al., 2023; Zhao et al., 2025). The current model links these results by considering knowledge conversion as the organisation's process for turning digital information into high-value activities.

At the same time, the results should not be generalised to suggest that all digital initiatives or all government interventions create value. A moderate construct shows that the respondents did not have uniformly favourable circumstances. The positive structural associations describe average associations within the sample, not guaranteed returns. The company may have poor project selection, legacy incompatibility, weak data governance, skill shortages, and policy dependence. A certain type of ability is that the environment offers a number of opportunities, and whether the organisation can make full use of these opportunities depends on its absorption capacity.

Contextual interpretation is not a ranking of regions or industries by competitiveness indices. The goal is not to find out which area in China has better diamonds. Instead, the analysis explores the impact of perceived good environment on the Economy of Manufacturing Enterprises. By linking ecosystem conditions to firm learning and value, this study provides a micro-foundational extension of research in the applied Diamond Model.

Practical implications

Assess the results of the capability in digital transformation, not the technology used. Implementation dashboards should monitor whether the digital project has enhanced environmental scanning, cross-functional interpretation, process experimentation, knowledge codification, and commercialisation. Other indicators of whether the transformation has built absorption capacity include the time from a customer signal to a process change, the reuse of supplier knowledge, experiment-to-scale conversion, and the adoption of lessons across plants.

Investment should have technical and organisational components. The technology infrastructure needs to invest in digital literacy, process ownership, incentives, and cross-functional cooperation simultaneously. Liu et al. (2023) believe that in the digital age, ”digital-era competence” should also include managerial, relational, and strategic capabilities in addition to technical knowledge. Therefore, the platform should be combined with role redesign, training, communities of practice, and routines to translate external knowledge into operating standards.

Promptly respond to changes in the external environment. Supplier co-development, university cooperation, industrial platforms, and customer feedback systems can all provide relevant knowledge. A partnership will only be advantageous if the focal firm has clear interfaces and internal owners of the acquired knowledge. Based on the results of the Diamond Model, enterprises can identify deficiencies in factor conditions, demand sophistication, supporting industries, rivalry, policy, and exposure to chance events, and adjust transformation priorities according to these environmental constraints.

Policymakers should not rely solely digital support and equipment subsidies. Infrastructure and funds are also required, and policies should raise the standards for interoperability, workforce training, demonstration networks, and access to special services. Based on the regional data, the three components of digital competitiveness are foundations, enterprises, and markets (Yang et al., 2024). Capability-oriented programmes can help small-scale manufacturers increase productivity by building infrastructure, and their scope of application is also expanding.

Absorptive-capacity indicators can provide managers and other parties with additional information on the level of digitalisation in the organisation. However, at present, perceptual evidence has failed to show that these indicators predict audited cash flows, market value, or investment returns; thus, this predictive ability has not been confirmed by independent research on financial data.

Limitations and future research

Some limitations constrain the results. First, the cross-sectional design cannot establish temporal ordering. Digitalisation can enhance the firm’s absorption capacity, and a higher absorption capacity may motivate further digitalisation. Longitudinal and cross-lagged designs are required to separate these processes and capture delayed value effects.

Second, the data are based on self-reported perceptions by a single informant in each enterprise. Harman’s test, the same-indicator one-factor CFA, and the common latent factor sensitivity analysis showed that the results were not fully due to a single common-method source, but statistical diagnostics could not rule out common-method variance, social desirability, or limited access to financial information. In the future, researchers can combine the survey data with objective indicators, such as digital investment, patents, new-product revenue, free cash flow, return on assets, Tobin’s Q, and market valuation. Multiple respondents per firm would also improve measurement reliability.

Third, a cross-sectional SEM cannot confirm the time sequence suggested by mediation. Bootstrap indirect effects quantify indirect associations in the specified covariance model and are not evidences of longitudinal processes. In the future, a longitudinal or cross-lagged design can be used to determine whether the same indirect path exists when the predictor, mediator, and outcome variables are measured at different times.

Fourth, despite having a relatively weak loading, the four-dimensional absorptive-capacity specification maintained assimilation. Replication will empirically determine whether assimilation varies by industry in Chinese manufacturing and examine measurement invariance across firm size, industry, ownership and region. The above tests will verify the consistency of the measurement system across these contexts.

Fifth, the Diamond Model is treated as an overall latent factor. This approach is parsimonious but may overlook the compensating effects of demand, factors, suppliers, rivalry, government, and chance. In the future, it will be explored whether the various components of the environment promote or hinder different stages of absorptive capacity, and how digitalisation changes this.

Finally, the sample includes some manufacturing enterprises but does not cover the entire country statistically. Research in other areas and countries has also explored how institutional systems change the dual-driver mechanism. Recently, research by East African SMEs has shown that capability mediation is context-independent but still vulnerable to technological disruption (Kobusingye et al., 2026).

Conclusion

This paper developed a quantitative model to examine the impact of digitalisation and competition on the perceived value of Chinese manufacturing enterprises. Digitalisation and Diamond Model factors were each positively associated with perceived enterprise value and absorptive capacity. Absorptive capacity, in turn, had the strongest direct associated with perceived enterprise value and considerable indirect effects of both antecedents. The relatively similar total associations suggest that firm-level transformation and ecosystem quality offer complementary, rather than competing, explanations for perceived value.

The first result of this study is that digital technology is not inherently associated with perceived value. Digital systems have expanded the range of information and strengthened coordination; favourable environments have provided resources, demand, suppliers, competition, and

institutional support. The firm associated with higher perceived enterprise value if it also has routines for acquiring, assimilating, transforming, and applying knowledge. Therefore, absorptive capacity serves as a common conversion mechanism for internal transformation and external opportunities into cash-flow quality, profitability, and sustainable development ability.

For the theory, the dual-driver model includes digital strategy, the resource-based view, national competitive advantage, dynamic capabilities, and absorptive capacity. Currently, the emphasis is on learning routines and ecosystem cooperation rather than technology application. The results support the assessment of transformation based on how many systems have been introduced and how often the organisation has been able to convert digital and external knowledge into enhanced perceived enterprise value.

Supplementary materials

The accompanying supplementary Word file contains five evidence sections: S1, complete 52-item descriptive and item-analysis statistics; S2, measurement-model results; S3, absorptive-capacity model comparisons and omission sensitivity; S4, common-method analyses; and S5, structural-model estimates, bootstrap indirect effects, and nested-model comparisons. No respondent-level dataset or native software output is included. Requests for de-identified data and analysis files should be directed to the corresponding author and remain subject to the original consent, ethics approval, journal policy, and data-use authorization.

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