The Impact of Digital Transformation on the Operational Performance of Small and Medium-sized Enterprises: The Mediating Effect of Organizational Agility

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Abstract

For small and medium-sized enterprises, digital transformation now occupies a central place on the strategic agenda, yet whether and how it translates into operational gains is still supported by fragmented empirical evidence. By drawing on the dynamic capability perspective, we examine the effect of digital transformation on the operational performance of small and medium-sized enterprises and test whether organizational agility serves as the transmission mechanism. Survey data from 412 small and medium-sized manufacturing and service firms are studied using hierarchical regression and bootstrap mediation testing. A significant positive effect of digital transformation on operational performance emerges from the results, and digital transformation is found to strengthen organizational agility considerably. Organizational agility partially mediates the link between the two constructs, and it accounts for 45.1 percent of the total effect. The indirect path turns out to be stronger among smaller firms and among manufacturing firms in the heterogeneity analysis, whereas the direct path is more pronounced among medium-sized firms. Stability of these findings is found to be robust when considering an alternative outcome measure and a lagged specification.

Keywords

Digital transformation, organizational agility, operational performance, small and medium-sized enterprises, mediating effect.

1. Introduction

We set out to examine systematically how digital transformation directly affects the operational performance of small and medium-sized enterprises and to identify the internal mechanism through which that effect is realised.

The overall effect of digital transformation on operational performance is examined here, and we clarify how integrating digital technology into operating processes, data infrastructure and decision routines is converted into measurable improvement in cost control, quality conformance, delivery reliability and process flexibility within resource-constrained firms. Organizational agility is then introduced as a mediating variable to test whether the capability to sense environmental change and to reconfigure operating resources transmits the influence of digital transformation towards operational outcomes. Given that small and medium-sized enterprises differ considerably in employment scale and industry attributes, we further examine whether such differences lead to significant differentiation in the intensity of the effect. By constructing and validating a theoretical analytical model that incorporates a mediating variable, a shortcoming of existing literature is addressed: prior work frequently reports a

direct association without opening the transmission path that connects technology deployment to operational outcomes.

An organizational change process in which digital technology redefines value creation paths, rather than a discrete act of technology procurement, is how digital transformation has been conceptualised [1]. The construct was subsequently broadened into a firm-wide reconfiguration of strategy, structure and business model that cuts across marketing, operations and information systems domains [2]. Scholarly output on the topic has expanded rapidly, as systematic reviews demonstrate, yet it remains dispersed across disciplines, and there is limited convergence on how transformation outcomes should be measured [3][4]. The same fragmentation is reported in a review of the current state of the art, which calls for designs that specify intervening organizational variables [5], and a review of the underlying technology stack similarly notes that the field is still consolidating around a shared set of outcome indicators [6].

A positive association between digital transformation and firm performance has been repeatedly documented in empirical work on listed firms. Using a sample of Chinese listed companies, Zhai and colleagues [7] reported that performance gains arise through operating efficiency and innovation output. From the perspective of public policy and innovation, Peng and Tao [8] demonstrated that enterprise performance benefits from digital transformation when an appropriate policy environment is in place. Zhang and colleagues [9] concentrated on manufacturing firms and demonstrated that the influence of digital transformation on corporate performance is transmitted through business model innovation, and innovation capability strengthens that relationship.

More recent and less settled is the evidence drawn from small and medium-sized enterprises. Gaglio and colleagues [10] studied firm-level data on manufacturing enterprises and reported that innovation activity and productivity rise with digital transformation, although the return differs across categories of technology. Digital orientation and digital capability were found by Rupeika-Apoga and colleagues [11] to jointly determine the degree of transformation that small firms can achieve under external disruption. Scuotto and colleagues [12] adopted a microfoundational perspective and traced the growth of small firms in the digital era to managerial cognition and to individual-level knowledge resources. From a dynamic capabilities perspective, Matarazzo and colleagues [13] demonstrated that capability development is required before digital channels can be converted into customer value.

A uniform positive relationship is not supported by all of the evidence. Blichfeldt and Faullant [14] examined process industry firms and found that the performance return to digital technology adoption depends on the type of product innovation and service innovation that the technology enables, meaning that adoption on its own is insufficient. This divergence points to the conclusion that the link between digital transformation and performance is conditional on an intervening organizational capability rather than direct and automatic.

As the most frequently suggested intervening capability, organizational agility has attracted considerable attention. Troise and colleagues [15] argued that agility allows small firms to navigate volatile and ambiguous environments during digital transformation. Digital platform capability was found by Ahmed and colleagues [16] to raise the agility of emerging market manufacturing small firms through intellectual capital, with environmental dynamism acting as a boundary condition. AlNuaimi and colleagues [17] identified a nexus among leadership, agility and digital strategy in which agility connects digital initiatives to strategic outcomes. On the conceptual side, Walter [18] consolidated a fragmented body of definitions, and Salmela and colleagues [19] reformulated agility for digital settings by separating the sensing of change from the reconfiguration of resources.

There are several limitations that remain in this body of work. Much of the available evidence comes from large listed firms whose resource endowment differs sharply from that of small and medium-sized enterprises. Agility is frequently invoked as an explanation without being modelled and estimated as an intervening variable within a single empirical framework. Furthermore, analyses seldom examine whether the transmission path itself varies with employment scale or with sector membership. By estimating a mediation model on primary survey data collected from small and medium-sized enterprises, by quantifying the share of the total effect that travels through organizational agility, and by comparing the estimated paths across scale-based and sector-based subsamples, we respond to these gaps.

What follows is organised as below. Section 2 defines the core constructs and sets out the theoretical foundation. Section 3 develops the research hypotheses and describes the research design, covering sample selection, variable design and model construction. Section 4 reports the empirical analysis, including descriptive statistics, reliability and validity assessment, correlation and multicollinearity diagnostics, regression estimation, mediation testing, heterogeneity analysis and robustness checks. Section 5 presents the research conclusions.

2. Conceptual Definition and Theoretical Foundation

2.1. Definition of Core Concepts

2.1.1. Digital Transformation

By deploying digital technology to reconstruct operating processes, information infrastructure and decision routines, an enterprise undertakes digital transformation, which redefines the path of value creation rather than merely accelerating it [1]. The construct is broader than information technology adoption because it encompasses structural adjustment, workflow redesign and the reallocation of decision rights, and it is broader than digitisation because it addresses the logic of value creation instead of the format of information [2]. Digitisation, digitalisation and digital transformation are distinguished in reviews of the field along an increasing scale of organizational depth, and transformation is placed at the level where the operating model itself is altered [6].

We treat digital transformation as a reflective construct measured at the firm level along three observable facets. These facets are the breadth of digital technology deployed in production and service delivery, the degree to which core operating processes are executed on an integrated digital platform, and the extent to which operating decisions are informed by systematically collected data. In the empirical models that follow, the construct is denoted by DT.

2.1.2. Organizational Agility

The capability of an enterprise to identify change in its competitive environment and to reconfigure resources and processes in response, with speed and at acceptable cost, constitutes organizational agility. A fragmented body of definitions was reviewed by Walter [18], who concluded that the construct consistently combines a perceptual element concerned with identifying change and an executional element concerned with redeploying resources. Salmela and colleagues [19] reformulated agility for digital settings and argued that digital infrastructure alters both elements, because sensing becomes continuous and reconfiguration becomes modular.

Sambamurthy and colleagues [20] advanced the digital options logic from which the construct originates theoretically; they argued that information technology investment creates process options and knowledge options exercised when competitive conditions shift, and agility is the mechanism through which technology investment reaches performance. Within the dynamic capability framework, Teece and colleagues [21] positioned agility and noted that it is costly,

so firms rationally acquire it in proportion to the uncertainty they face. In the empirical models, organizational agility is denoted by OA.

2.1.3. Operational Performance

The achievement of an enterprise on the operating dimensions that its production and service systems are designed to deliver constitutes operational performance. Unit cost, quality conformance, delivery reliability and process flexibility are the dimensions adopted here, each assessed relative to the main competitors of the responding firm. A comparable operational framing was used by Yang and colleagues [22] when examining the impact of digital technology adoption in supply chains, and they reported that operating outcomes respond to technology deployment sooner than financial outcomes.

There are two reasons why operational rather than financial indicators are appropriate in the present setting. Small and medium-sized enterprises are frequently unlisted, so audited financial data are not uniformly available. Operating outcomes are also closer in the causal chain to process-level change, and they are therefore less contaminated by financing structure and by market sentiment. In the empirical models, operational performance is denoted by OP.

2.2. Basic Theoretical Support

2.2.1. Resource based View

Sustained advantage, according to the resource based view, originates in resources that are valuable, rare, imperfectly imitable and difficult to substitute. Digital technology on its own rarely satisfies these conditions, because hardware and standard software are available on open factor markets. For artificial intelligence capability, Mikalef and Gupta [23] demonstrated that performance value arises from the combination of tangible resources, human skills and intangible organizational assets rather than from the technology alone. The implication for the present study is that digital transformation should influence operational performance mainly through an organizational capability that is jointly produced by technology and by complementary assets.

2.2.2. Dynamic Capability Theory

How enterprises renew their resource base under environmental change is the concern of dynamic capability theory, which decomposes that renewal into sensing, seizing and reconfiguring. Ghosh and colleagues [24] used the framework in industrial firms and demonstrated that digital transformation is realised through the accumulation of sensing and reconfiguring routines rather than through technology procurement. A comparable sequence was traced by Chirumalla [25] in process industries, where digitally enabled process innovation required the deliberate construction of new capabilities. Teece and colleagues [21] identified agility as the observable expression of dynamic capability under uncertainty. The central logic of the present model is supplied by this theory: digital transformation builds a dynamic capability, and the capability rather than the technology gives rise to the operational outcome.

2.2.3. Information Processing Theory

According to information processing theory, organizational effectiveness depends on the fit between the information processing requirement imposed by the environment and the information processing capacity that the organization has built. Capacity is raised by digital transformation through wider data collection, shorter transmission latency and automated routine interpretation. Panda and Rath [26] demonstrated that information technology capability and knowledge management capability jointly raise organizational agility, and that environmental factors condition the strength of that relationship. Under this logic, agility is the organizational expression of an elevated information processing capacity, and this explains why it should transmit the effect of digital transformation.

2.2.4. Contingency Theory

No organizational configuration is universally superior under contingency theory; the performance of a given configuration depends on the conditions under which it operates. Ahmed and colleagues [16] reported that environmental dynamism conditions the conversion of digital platform capability into agility among emerging market manufacturing firms. A conceptual framework in which strategic agility is contingent on the volatility of the operating environment was developed by Shams and colleagues [27]. The inclusion of environmental dynamism as a control variable and the heterogeneity analysis conducted across employment scale and sector membership are motivated by this theory.

3. Research Hypotheses and Research Design

3.1. Research Hypotheses

3.1.1. The Impact of Digital Transformation on Operational Performance

Three connected channels are expected to carry the positive effect of digital transformation on operational performance. Process integration removes manual handoffs between functions and therefore reduces the buffer inventory and the rework that arise from information delay. By narrowing the gap between the state of the operating system and the information available to the decision maker, data-driven decision making improves scheduling accuracy and lowers unit cost. Modular digital infrastructure lowers the marginal cost of introducing product variants and raises process flexibility without a proportional increase in overhead.

This reasoning is broadly consistent with the available empirical evidence. Positive performance effects among listed firms were reported by Zhai and colleagues [7] and by Peng and Tao [8], and the same direction was documented among manufacturing enterprises by Zhang and colleagues [9]. Productivity gains among manufacturing small firms were found by Gaglio and colleagues [10]. Amankwah-Amoah and colleagues [28] observed that the accelerated digitalisation brought about by external disruption led to durable improvement in the operating routines of firms that had already begun the transition. An association between digital orientation in small firms and superior innovation performance, which is an antecedent of operating improvement, was demonstrated by Ardito and colleagues [29]. Blichfeldt and Faullant [14] reported a weaker association in the process industry, which indicates that the magnitude rather than the direction of the effect is in dispute. The following hypothesis is therefore suggested.

H1: Digital transformation has a significant positive effect on the operational performance of small and medium-sized enterprises.

3.1.2. The Impact of Digital Transformation on Organizational Agility

Both elements of the construct are strengthened by digital transformation, which is why it is expected to raise organizational agility. Sensing improves because instrumented processes and integrated customer channels shorten the interval between a change in demand or supply conditions and the recognition of that change inside the firm. Reconfiguration improves because modular architectures and standardised interfaces reduce the switching cost of redirecting capacity, so that a response can be executed without renegotiating the whole operating system. This reasoning was formalised by Sambamurthy and colleagues [20], who described technology investment as the purchase of process options and knowledge options exercised when conditions change.

In small firm settings, recent evidence supports the proposition. Troise and colleagues [15] found that firms further advanced in digital transformation displayed higher agility under volatile conditions. Digital platform capability was reported by Ahmed and colleagues [16] to raise the agility of emerging market manufacturing small firms. Del Giudice and colleagues [30]

demonstrated that smart manufacturing configurations in small firms increase the speed at which digital innovation is absorbed into operations. On conceptual grounds, Salmela and colleagues [19] argued that digital infrastructure changes the nature of agility rather than merely its level. The following hypothesis is therefore suggested.

H2: Digital transformation has a significant positive effect on the organizational agility of small and medium-sized enterprises.

3.1.3. The Mediating Role of Organizational Agility

The relationship between digital transformation and operational performance is expected to be mediated by organizational agility. Technology deployment alters the information environment of the firm, but the operating result depends on whether the firm converts improved information into a faster and better targeted response. It is agility that performs this conversion. AlNuaimi and colleagues [17] described the sequence explicitly, placing agility between digital strategy and strategic outcomes. Performance was identified by Walter [18] as the outcome most frequently associated with agility across the reviewed literature. Teece and colleagues [21] treated agility as the mechanism through which capability investment is realised under uncertainty, and Panda and Rath [26] gave evidence that capability-based antecedents reach performance through agility.

A residual direct path is nonetheless expected to remain. Some benefits of digital transformation, such as the automation of clerical work and the elimination of duplicate data entry, accrue without any adaptive response and therefore bypass agility. Accordingly, partial rather than complete mediation is predicted. The following hypothesis is therefore suggested.

H3: Organizational agility plays a mediating role in the effect of digital transformation on the operational performance of small and medium-sized enterprises.

Figure 1 presents the theoretical model integrating the three hypotheses. Digital transformation is placed as the antecedent, organizational agility as the mediator and operational performance as the outcome, with environmental dynamism, firm size, firm age and industry attribute entering as control variables.

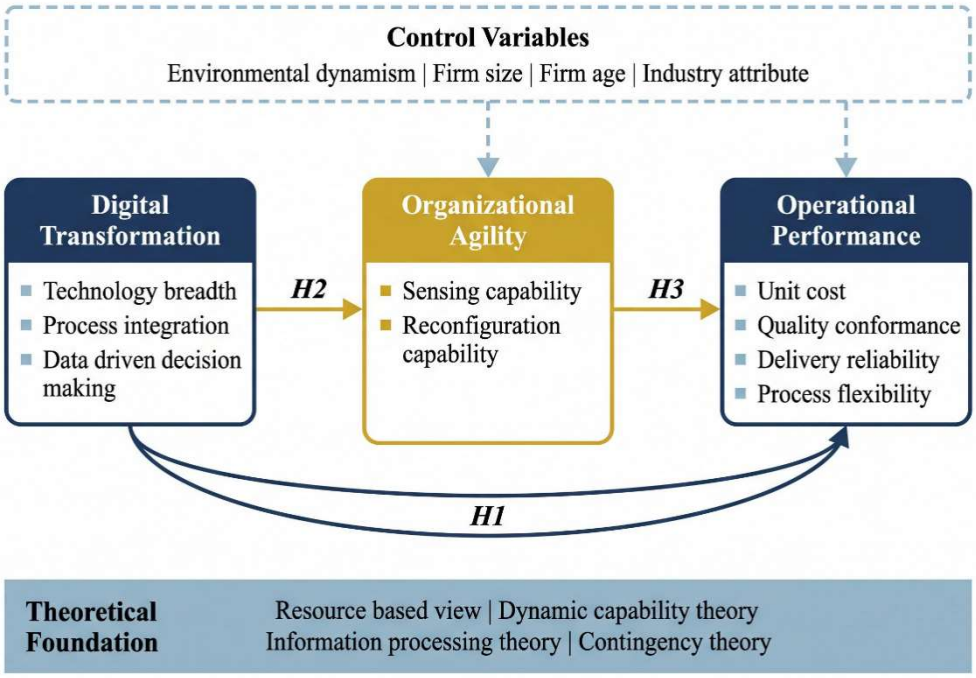


Figure 1. Research Model

3.2. Sample Selection and Data Sources

Primary data were collected through a structured questionnaire administered to small and medium-sized enterprises in manufacturing and producer services. The sampling frame was assembled from municipal enterprise registries and from the membership lists of industry associations, and enterprises were retained in the frame when the number of full-time employees fell between 20 and 300, corresponding to the small and medium classification applied in the surveyed jurisdictions. Senior managers, middle managers and department heads with direct responsibility for operations were addressed by the questionnaire, because these respondents hold the process-level knowledge required to assess the measured constructs.

The specific screening steps are as follows. (1) Enterprises established for fewer than two years are excluded, because their operating routines are not yet stable. (2) Questionnaires in which the respondent reported no involvement in operating decisions are excluded. (3) Questionnaires with missing values on any construct item or with an invariant response pattern across reverse-worded items are excluded. Out of 520 distributed questionnaires, 412 valid responses were retained, and this gives an effective response rate of 79.2 percent. The requirement that the number of observations should exceed ten times the largest number of predictors directed at any single construct is satisfied by the sample size [31].

At the design stage, procedural remedies against common method bias were applied, including separating the predictor and criterion sections of the instrument, assuring respondent anonymity and including reverse-worded items [32]. Statistical assessment was conducted after data collection and is reported in Section 4.2. By comparing the earliest quartile and the latest quartile of returned questionnaires on all construct means, non-response bias was assessed, and no significant difference was found. Table 1 reports the demographic profile of the valid sample.

Table 1. Sample Profile

Characteristic	Category	Frequency	Percentage
Industry attribute	Manufacturing	236	57.3
	Producer services	176	42.7
Employment scale	Fewer than 100 employees	224	54.4
	100 to 300 employees	188	45.6
Firm age	10 years or below	179	43.4
	Above 10 years	233	56.6
Respondent position	Senior manager	142	34.5
	Middle manager	197	47.8
	Department head	73	17.7
Total		412	100.0

3.3. Variable Design

Multiple-item scales adapted from validated instruments were used to measure all latent constructs, and every item was scored on a seven-point Likert scale anchored at complete disagreement and complete agreement. Six items covering technology breadth, process integration and data-driven decision making were used for digital transformation, adapted from the operationalisations used by Rupeika-Apoga and colleagues [11] and from the review of measurement practice reported by Zhu and colleagues [6]. Six items separating the sensing

of environmental change from the reconfiguration of operating resources were used for organizational agility, adapted from Salmela and colleagues [19] and Panda and Rath [26]. Five items covering unit cost, quality conformance, delivery reliability and process flexibility relative to the main competitors were used for operational performance, adapted from Yang and colleagues [22] and Blichfeldt and Faullant [14]. Four items adapted from Ahmed and colleagues [16] were used for environmental dynamism.

Registry records rather than the questionnaire supplied firm size, firm age and industry attribute, which reduces the proportion of the covariance matrix exposed to common method variance. Firm size is the natural logarithm of the number of full-time employees, firm age is the number of years since establishment, and industry attribute is a dummy variable that equals one for manufacturing and zero for producer services. Table 2 reports the full variable specification.

Table 2. Variable Definition and Measurement

Variable	Symbol	Items	Operational definition	Adapted from
Digital transformation	*DT*	6	Breadth of digital technology in operations, integration of core processes on a common digital platform, and reliance on systematically collected data in operating decisions	[6][11]
Organizational agility	*OA*	6	Capability to detect change in demand, supply and technology conditions and to reconfigure operating resources with speed and at acceptable cost	[19][26]
Operational performance	*OP*	5	Achievement in unit cost, quality conformance, delivery reliability and process flexibility relative to the main competitors	[14][22]
Environmental dynamism	*ED*	4	Perceived rate and unpredictability of change in technology, customer demand and competitive conduct	[16]
Firm size	*FSize*	1	Natural logarithm of the number of full-time employees	Registry record
Firm age	*FAge*	1	Number of years since establishment	Registry record
Industry attribute	*Ind*	1	Dummy variable equal to one for manufacturing and zero for producer services	Registry record

Note: all latent constructs were measured on a seven-point Likert scale.

3.4. Model Construction

Three sets of multiple linear regression models are constructed for empirical testing in order to verify the effect of digital transformation on operational performance and the mediating role of organizational agility in the transmission path. The subscript i indexes the responding enterprise in all specifications.

The direct effect of digital transformation on the operational performance of small and medium-sized enterprises is examined by Model (1), which therefore serves to verify research hypothesis H1.

$$OP_i = \beta_0 + \beta_1 DT_i + \beta_2 ED_i + \beta_3 FSize_i + \beta_4 FAge_i + \beta_5 Ind_i + \varepsilon_i \quad (1)$$

The relationship between digital transformation and organizational agility is analysed by Model (2), which therefore serves to verify research hypothesis H2.

$$OA_i = \gamma_0 + \gamma_1 DT_i + \gamma_2 ED_i + \gamma_3 FSize_i + \gamma_4 FAge_i + \gamma_5 Ind_i + \mu_i \quad (2)$$

The mediating effect of organizational agility in the process through which digital transformation affects operational performance is tested by Model (3), which therefore serves to verify research hypothesis H3.

$$OP_i = \delta_0 + \delta_1 DT_i + \delta_2 OA_i + \delta_3 ED_i + \delta_4 FSize_i + \delta_5 FAge_i + \delta_6 Ind_i + \nu_i \quad (3)$$

By multiplying the coefficient of digital transformation in Model (2) by the coefficient of organizational agility in Model (3), the indirect effect transmitted through organizational agility is obtained, and the total effect is the sum of the indirect effect and the residual direct effect estimated in Model (3). The two quantities are defined in Equation (4), where IE denotes the indirect effect and TE denotes the total effect.

$$IE = \gamma_1 \times \delta_2 \qquad TE = \delta_1 + \gamma_1 \times \delta_2 \quad (4)$$

How much of the total effect travels through organizational agility is expressed by the variance accounted for statistic, denoted VAF

$$VAF = \frac{\gamma_1 \delta_2}{\gamma_1 \delta_2 + \delta_1} \quad (5)$$

Using the bias-corrected bootstrap procedure with 5000 resamples, we assess the statistical significance of the indirect effect; this procedure does not impose a normality assumption on the sampling distribution of the product term and therefore gives a more accurate confidence interval than the normal-theory alternative [33]. When the bootstrap confidence interval excludes zero, the indirect effect is treated as significant.

4. Empirical Analysis

4.1. Descriptive Statistical Analysis

Descriptive statistics were computed on the 412 valid observations to characterise the distribution of the sample and the dispersion of the measured constructs. Table 3 presents the corresponding results.

Table 3. Descriptive Statistics Results

Variable	Obs	Mean	Std. Dev.	Min	Max
DT	412	4.862	1.024	1.667	6.833
OA	412	4.713	0.981	1.833	6.667
OP	412	4.935	0.942	2.200	6.800
ED	412	4.551	1.073	1.500	6.750
FSize	412	4.418	1.126	2.303	5.704
FAge	412	11.624	6.837	2.000	34.000
Ind	412	0.573	0.495	0.000	1.000

4.2. Reliability and Validity Analysis

The Cronbach coefficient and composite reliability were used to assess internal consistency. Composite reliability is preferred for reflective constructs because it weights each indicator by its standardised loading rather than assuming equal contribution, and it is defined in Equation (6), where λ_i denotes the standardised loading of indicator i on its assigned construct.

$$CR = \frac{(\Sigma\lambda_i)^2}{(\Sigma\lambda_i)^2 + \Sigma\left(1 - \lambda_i^2\right)} \tag{6}$$

The average variance extracted, which reports the share of indicator variance explained by the construct, was used to assess convergent validity. Equation (7) defines the statistic, where n denotes the number of indicators assigned to the construct.

$$AVE = \frac{\Sigma\lambda_i^2}{n} \tag{7}$$

Table 4. Reliability and Convergent Validity Results

Construct	Item	Loading	Cronbach coefficient	Composite reliability	Average variance extracted
Digital transformation	DT1	0.812	0.897	0.921	0.661
	DT2	0.836			
	DT3	0.791			
	DT4	0.847			
	DT5	0.803			
	DT6	0.788			
Organizational agility	OA1	0.795	0.884	0.915	0.643
	OA2	0.821			
	OA3	0.808			
	OA4	0.774			
	OA5	0.832			
	OA6	0.786			
Operational performance	OP1	0.783	0.871	0.907	0.621
	OP2	0.812			
	OP3	0.796			
	OP4	0.769			
	OP5	0.788			
Environmental dynamism	ED1	0.804	0.842	0.894	0.628
	ED2	0.781			
	ED3	0.815			
	ED4	0.767			

Table 4 reports the estimation results. All standardised loadings lie between 0.767 and 0.847, exceeding the threshold of 0.700. The Cronbach coefficient ranges from 0.842 to 0.897 and composite reliability from 0.894 to 0.921, so every construct satisfies the conventional threshold of 0.700 for internal consistency. With values ranging from 0.621 to 0.661, the average variance extracted exceeds the threshold of 0.500 for all four constructs, and convergent validity is therefore established [34].

The criterion of Fornell and Larcker [34] and the heterotrait-monotrait ratio of correlations were used to assess discriminant validity, and Table 5 reports the results. On the diagonal, the square root of the average variance extracted exceeds every correlation in the corresponding row and column, and every heterotrait-monotrait ratio lies below the conservative threshold of 0.850 recommended for conceptually related constructs [35]. Discriminant validity is therefore established.

Table 5. Discriminant Validity Results

Construct	*DT*	*OA*	*OP*	*ED*
DT	0.813	0.586	0.541	0.352
OA	0.521	0.802	0.618	0.328
OP	0.478	0.546	0.788	0.276
ED	0.312	0.287	0.241	0.792

Note: values on the diagonal in bold are the square root of the average variance extracted; values below the diagonal are construct correlations; values above the diagonal are heterotrait-monotrait ratios.

After the procedural remedies described in Section 3.2, common method bias was evaluated statistically. The unrotated single factor solution accounts for 32.7 percent of the total variance, which is below the reference level of 40 percent. A maximum variance inflation factor of 2.14 across all constructs is returned by the full collinearity assessment, which is below the reference level of 3.30. Neither diagnostic indicates that common method variance threatens the interpretation of the estimates [32].

4.3. Correlation and Multicollinearity Analysis

Pairwise correlation results for all variables in the sample are presented in Figure 2. Between the explained variable OP and the core explanatory variable DT, the correlation coefficient is 0.478 and is significantly positive at the 1 percent level, which gives preliminary support for the expected positive effect of digital transformation on operational performance. Between OP and the mediating variable OA, the correlation coefficient is 0.546 and is also significantly positive at the 1 percent level, while the correlation between DT and OA is 0.521 under the same significance level. A transmission path in which digital transformation reaches operational performance through organizational agility is consistent with this pattern. Between ED and the three focal constructs, correlations are positive but comparatively weak, ranging from 0.241 to 0.312.

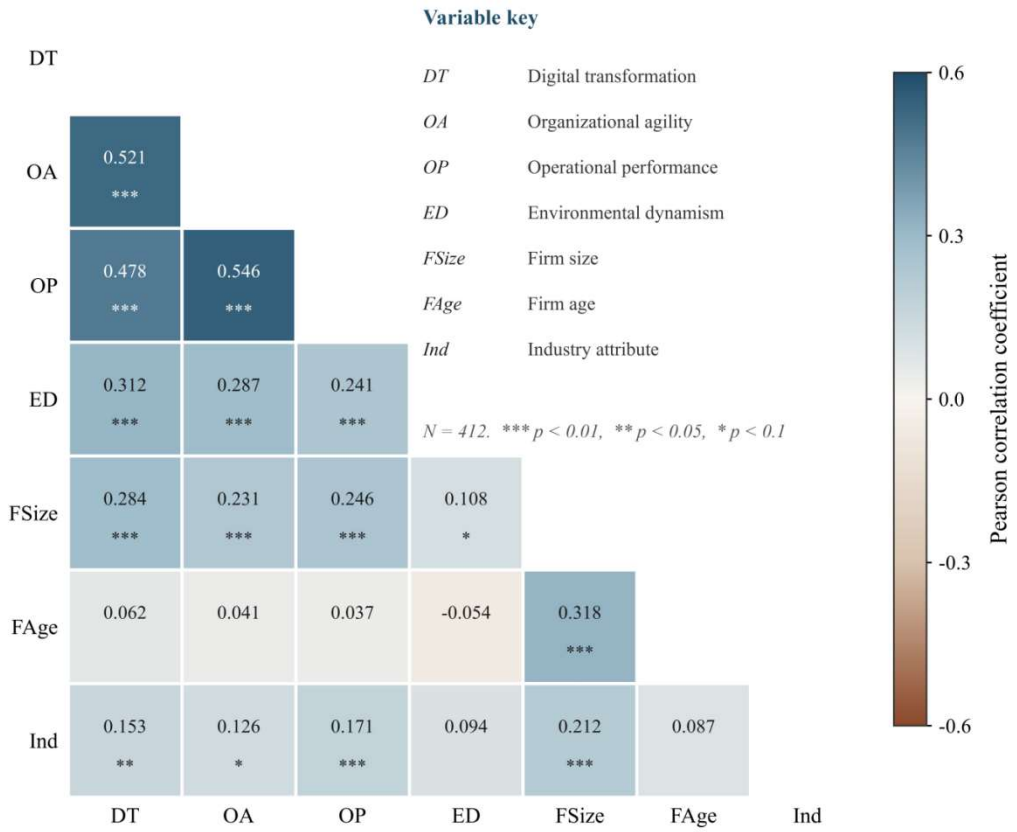


Figure 2. Pairwise Correlations Results

The variance inflation factor was computed for each regressor to avoid serious collinearity among the selected variables. Equation (8) defines the statistic, where R_j^2 denotes the coefficient of determination obtained by regressing regressor *j* on all remaining regressors in the model.

$$VIF_j = \frac{1}{1 - R_j^2} \tag{8}$$

Table 6 shows that the mean variance inflation factor of the sample variables is 1.28 and the maximum value is 1.51, both far below the conventional cut-off of 10 and also below the more demanding cut-off of 5. No pronounced multicollinearity is therefore found among the variables included in the regression models.

Table 6. Multicollinearity Analysis

Variable	*VIF*	1/*VIF*
OA	1.51	0.662
DT	1.42	0.704
FSize	1.28	0.781
ED	1.19	0.840
FAge	1.16	0.862
Ind	1.11	0.901
Mean *VIF*	1.28	

4.4. Multiple Linear Regression Analysis

4.4.1. The Impact of Digital Transformation on Operational Performance

The regression results for the main effect of digital transformation on operational performance are reported in Table 7. When only the core explanatory variable enters the specification, Column (1) shows that the regression coefficient of DT is 0.446 and is significantly positive at the 1 percent level. After introducing all control variables, Column (2) shows that the regression coefficient of DT is 0.412 and remains significant at the 1 percent level, while the coefficient of determination rises from 0.229 to 0.312. Support for the direct effect of digital transformation on the operational performance of small and medium-sized enterprises is therefore established, and research hypothesis H1 is verified.

Table 7. Regression Results of the Main Effect

Variable	(1) *OP*	(2) *OP*
DT	0.446*** (10.412)	0.412*** (9.876)
ED		0.084* (1.912)
FSize		0.126*** (2.874)
FAge		-0.041 (-0.938)
Ind		0.093** (2.147)
Constant	2.766*** (13.284)	1.842*** (5.316)
N	412	412
R^2	0.229	0.312
Adjusted R^2	0.227	0.303
F	121.836	36.782

Note: *** p<0.01, ** p<0.05, * p<0.1; values in parentheses are t statistics.

4.4.2. Mediating Effect Analysis of Organizational Agility

Table 8. Regression Results of the Mediating Effect

Variable	(1) *OP*	(2) *OA*	(3) *OP*
DT	0.412*** (9.876)	0.487*** (11.243)	0.226*** (5.018)
OA			0.382*** (8.437)
ED	0.084* (1.912)	0.112** (2.483)	0.041 (0.978)
FSize	0.126*** (2.874)	0.098** (2.216)	0.089** (2.134)
FAge	-0.041 (-0.938)	-0.028 (-0.624)	-0.030 (-0.716)
Ind	0.093** (2.147)	0.071 (1.598)	0.066 (1.572)
Constant	1.842*** (5.316)	1.516*** (4.278)	1.263*** (3.842)
N	412	412	412
R^2	0.312	0.341	0.408
F	36.782	42.019	46.531

Note: *** p<0.01, ** p<0.05, * p<0.1; values in parentheses are t statistics.

Table 8 reports the mediation estimation results. In Model (2), the regression coefficient of DT on organizational agility is 0.487 and is significantly positive at the 1 percent level, which

indicates that digital transformation raises the capability of the enterprise to sense change and to reconfigure operating resources. Research hypothesis H2 is therefore verified. When digital transformation and organizational agility enter jointly in Model (3), the coefficient of OA is 0.382 and is significant at the 1 percent level, while the coefficient of DT falls to 0.226 and remains significant at the 1 percent level. Relative to the coefficient of 0.412 obtained in Model (1), this reduction indicates that organizational agility carries part but not all of the influence of digital transformation, so partial mediation is established and research hypothesis H3 is verified.

Using the bias-corrected bootstrap procedure defined in Section 3.4, the magnitude and significance of the transmitted effect were assessed, and Table 9 reports the results. Computed according to Equation (4), the indirect effect equals 0.186 with a bootstrap standard error of 0.034, and the 95 percent confidence interval ranges from 0.124 to 0.257, excluding zero. The direct effect of 0.226 also remains significant, which confirms partial mediation. Computed according to Equation (5), the variance accounted for statistic equals 0.451, so 45.1 percent of the total effect of digital transformation on operational performance travels through organizational agility. This value falls within the interval conventionally interpreted as partial mediation.

Table 9. Bootstrap Results of the Indirect Effect

Effect	Path	Coefficient	Boot Std. Err.	Boot 95 percent LLCI	Boot 95 percent ULCI
Direct effect	*DT* to *OP*	0.226	0.045	0.138	0.314
Indirect effect	*DT* to *OA* to *OP*	0.186	0.034	0.124	0.257
Total effect	*DT* to *OP*	0.412	0.042	0.330	0.494

Note: bias-corrected bootstrap based on 5000 resamples; the indirect effect accounts for 45.1 percent of the total effect.

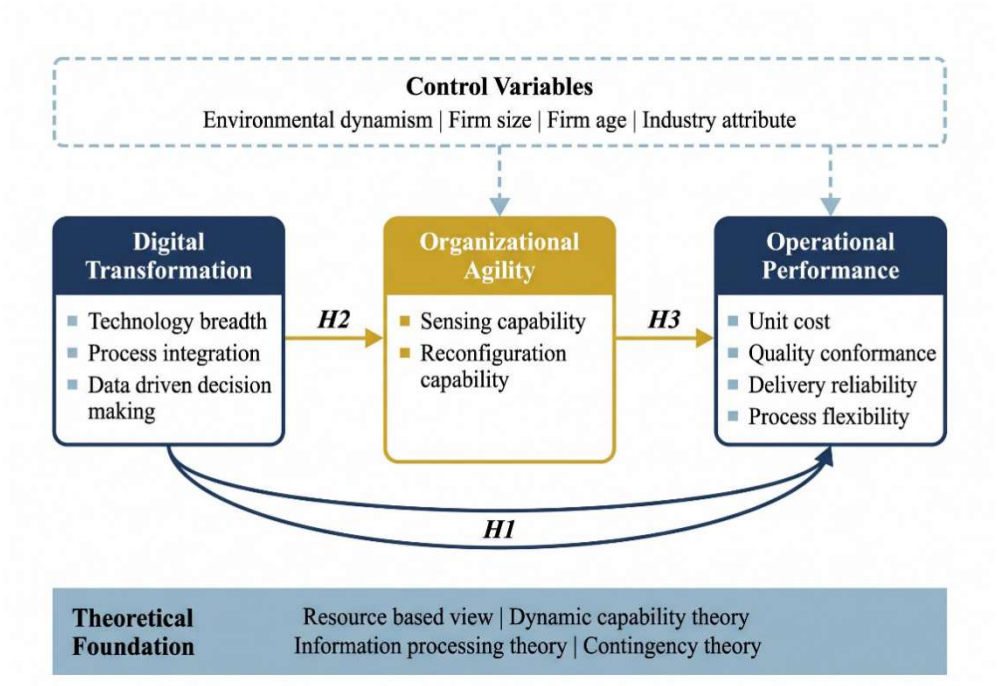


Figure 3. Path Coefficients of the Structural Model

Figure 3 graphically summarises the estimated structural paths, reporting the standardised coefficient of each path together with its significance level and displaying the decomposition of the total effect into its direct and indirect portions.

4.5. Heterogeneity Analysis

By splitting the full sample according to employment scale and according to industry attribute and re-estimating the mediation model within each subsample, the heterogeneity results presented in Table 10 were obtained. To test whether the paths differ significantly across groups, the permutation-based multigroup comparison procedure was used [36].

Across employment scale, a stronger path from digital transformation to organizational agility emerges among smaller enterprises, with a coefficient of 0.512 against 0.451 for medium-sized enterprises, and the path from organizational agility to operational performance follows the same pattern, with coefficients of 0.416 and 0.337 respectively. The residual direct path is reversed, since the coefficient of 0.271 recorded by medium-sized enterprises exceeds the coefficient of 0.184 recorded by smaller enterprises, and the difference of 0.087 is significant at the 5 percent level. The indirect effect accordingly accounts for 53.7 percent of the total effect among smaller enterprises against 35.9 percent among medium-sized enterprises. One plausible reading is that smaller enterprises possess shorter command chains and therefore convert digital capability into adaptive response more readily, whereas medium-sized enterprises obtain a larger share of the benefit through direct automation of standardised administrative work.

Table 10. Heterogeneity Analysis Results

Path or statistic	Small firms	Medium firms	Manufacturing	Producer services
DT to *OA*	0.512*** (8.124)	0.451*** (7.036)	0.503*** (8.436)	0.462*** (6.518)
OA to *OP*	0.416*** (6.802)	0.337*** (5.117)	0.401*** (6.914)	0.352*** (5.246)
DT to *OP*	0.184*** (2.914)	0.271*** (4.128)	0.248*** (4.102)	0.196*** (2.847)
Indirect effect	0.213	0.152	0.202	0.163
Boot 95 percent CI	[0.132, 0.308]	[0.084, 0.235]	[0.128, 0.291]	[0.091, 0.248]
VAF	0.537	0.359	0.449	0.454
R^2 for *OP*	0.394	0.421	0.417	0.386
N	224	188	236	176

Note: *** p<0.01, ** p<0.05, * p<0.1; values in parentheses are t statistics; small firms employ fewer than 100 staff and medium firms employ 100 to 300 staff.

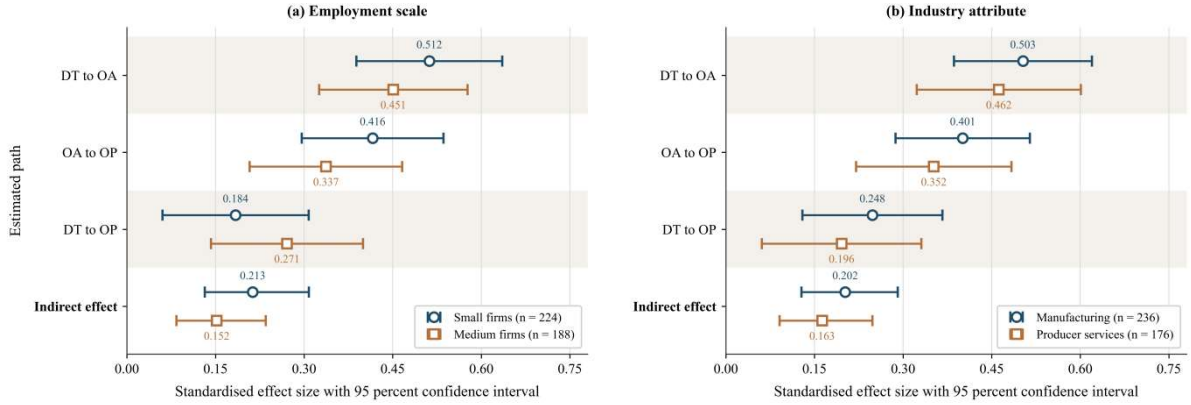


Figure 4. Comparison of Indirect Effects Across Subsamples

A similar ordering with a narrower gap emerges from the comparison across industry attribute. The path from organizational agility to operational performance is 0.401 in manufacturing against 0.352 in producer services, and the residual direct path is 0.248 against 0.196. In manufacturing, the indirect effect accounts for 44.9 percent of the total effect, and in producer services it accounts for 45.4 percent, so the relative importance of the transmission mechanism is comparable across sectors even though the absolute magnitude of every path is larger in manufacturing. Figure 4 displays the subsample comparison of the indirect effects.

4.6. Robustness Analysis

4.6.1. Replace the Explained Variable

To verify that the estimated relationship is not an artefact of the particular operating dimensions selected, a growth-oriented outcome measure replaced the explained variable. The replacement variable, denoted GROW, records the self-assessed growth of sales revenue over the preceding three years relative to the main competitors and was scored on the same seven-point scale. Panel A of Table 11 shows that the coefficient of OA is 0.365 and the residual coefficient of DT is 0.213, both significant at the 1 percent level, while the indirect effect is 0.178 with a bootstrap confidence interval from 0.116 to 0.249 that excludes zero. The variance accounted for statistic is 0.455, which is close to the value of 0.451 obtained in the baseline estimation. The core conclusions are therefore not sensitive to the choice of outcome measure.

4.6.2. One Period Lag Treatment

In order to mitigate the concern that the observed association reflects reverse causality or contemporaneous common method variance, a lagged specification was estimated. A follow-up wave of the questionnaire was administered to a subsample of 186 enterprises twelve months after the initial collection, and the outcome variable measured in the later wave was regressed on the explanatory variable and the mediator measured in the earlier wave. Temporal separation of the predictor and the criterion is among the procedural remedies recommended for reducing method-induced covariance [32]. Panel B of Table 11 shows that the coefficient of OA is 0.348 and the residual coefficient of DT is 0.209, both significant at the 1 percent level, and that the indirect effect of 0.164 retains a confidence interval that excludes zero. At 0.440, the variance accounted for statistic is marginally lower than the baseline value, consistent with the mild attenuation expected when predictor and criterion are separated in time. Good stability is therefore displayed by the core research conclusions, and endogeneity concerns do not appear to interfere substantively with the empirical results [37].

Table 11. Robustness Test Results

Path or statistic	Panel A: replaced explained variable	Panel B: one period lag treatment
DT to OA	0.487*** (11.243)	0.471*** (7.892)
OA to outcome	0.365*** (7.884)	0.348*** (5.216)
DT to outcome	0.213*** (4.612)	0.209*** (3.427)
Indirect effect	0.178	0.164
Boot 95 percent CI	[0.116, 0.249]	[0.094, 0.248]
VAF	0.455	0.440
Control variables	Included	Included
R^2	0.372	0.351
N	412	186

Note: *** p<0.01, ** p<0.05, * p<0.1; values in parentheses are t statistics; the outcome in Panel A is GROW and the outcome in Panel B is OP measured in the follow-up wave.

5. Research Conclusion

Survey data collected from 412 small and medium-sized enterprises in manufacturing and producer services serve as the research sample for empirically testing the mechanism of action between digital transformation and operational performance. A significant positive driving effect of digital transformation on the operational performance of small and medium-sized enterprises emerges from the results. Deeper deployment of digital technology in operating processes, tighter integration of core processes on a common platform and greater reliance on systematically collected data are directly converted into measurable improvement in cost control, quality conformance, delivery reliability and process flexibility. The main effect hypothesis is therefore effectively verified.

Turning to the transmission mechanism, partial mediation by organizational agility is found in the association between the two focal constructs. Digital transformation not only promotes operational performance directly but also contributes indirectly by strengthening the capability of the enterprise to identify environmental change and to reconfigure operating resources. The indirect path accounts for 45.1 percent of the total effect, and the bootstrap confidence interval excludes zero, so the complete transmission path is supported by empirical evidence. A significant direct path is retained, indicating that a portion of the benefit accrues through the automation of routine work without requiring any adaptive organizational response, which explains why the mediation is partial rather than complete.

Significant differences in the estimated paths are produced by employment scale and industry attribute, as the heterogeneity test results show. The transmission through organizational agility is more prominent in enterprises with fewer than 100 employees, where it accounts for 53.7 percent of the total effect, whereas the residual direct path is stronger in enterprises employing between 100 and 300 staff. Larger coefficients on every path are recorded by manufacturing enterprises than by producer services, although the relative share carried by the indirect route is comparable across the two sectors. Good stability is displayed by the core research conclusions when the explained variable is replaced with a growth-oriented outcome measure and when a lagged specification is estimated on a follow-up subsample.

By specifying and estimating the capability-based mechanism that connects digital transformation to operating outcomes in the small and medium-sized enterprise context, where prior evidence has been drawn predominantly from large listed firms, we make the theoretical contribution. Technology deployment is found to be a necessary but insufficient condition for operational improvement, which supports the dynamic capability reading of digital transformation and qualifies accounts that treat technology adoption as directly productive. The share of the total effect that travels through organizational agility is quantified and compared across subsamples, and this supplies an empirical basis for the observation that the barriers to digital transformation differ systematically across firm categories.

For managers, the implication is that investment in digital infrastructure should be accompanied by deliberate construction of sensing and reconfiguration routines, since the returns to technology are conditional on the capability that converts information into response. Smaller enterprises should prioritise the agility route, because their shorter command chains allow rapid conversion of digital capability into adaptive action. A larger share of the benefit is obtained by medium-sized enterprises through direct process automation, and they should therefore sequence their investment towards the standardisation of administrative work before pursuing broader adaptive redesign.

These conclusions are qualified by several limitations that also indicate directions for further work. The measurement of the latent constructs relies on perceptual reports supplied by a single respondent in each enterprise, and although procedural and statistical remedies were applied, the incorporation of objective operating records would strengthen the evidence.

Manufacturing and producer services within a single institutional environment bound the sample, so generalisation to other sectors and jurisdictions requires additional testing. Organizational agility is also treated as a single mediating capability in the design, whereas the sensing and reconfiguration elements may operate through distinct routes with different lags, which points to a longitudinal design capable of separating those elements as a productive extension.

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