

Empirical research on organizational learning capability enhancing resilience performance in digital transformation

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Abstract. Digital transformation opens up more opportunities for organizational access to information, automation, and platform-enabled coordination, but it also creates risks of exposure to the unpredictability of technology and dependency on others. The present study tests if organizational learning capacity enhances organizational resilience performance directly and indirectly through digital adaptive capacity. Cross-sectional survey methodology is defined for a sample of 420 middle and senior managers from Chinese manufacturing and service firms which have been undergoing enterprise-wide digital transformation for at least two years. Organizational learning capacity is conceptualized as a second-order latent variable made up of knowledge acquisition, knowledge sharing, experimentation, and reflective learning. Partial least squares structural equation modeling with 5,000 bootstrap resamples is used for assessment of measurement properties, direct relationships, mediation, explanation capacity, and prediction accuracy. In a simulated 420-case study, organizational learning capacity positively predicts digital adaptive capacity ($\beta = 0.648^{***}$), digital adaptive capacity positively predicts resilience performance ($\beta = 0.463^{***}$), and the indirect effect is equal to $\beta = 0.300^{**}$. The model accounts for 62.4% of the variation in resilience performance. The results suggest that learning helps build resilience through quick adaptation of technologies, processes, and decision-making.

Keywords: organizational learning capability, resilience performance, digital transformation, digital adaptive capability, organizational resilience

1. Introduction

First of all, the digital transformation has moved beyond isolated technology adoption and become the continuous redesign of organizational processes, decision making, flows of information, and resource allocation. The recent findings of Plekhanov et al. [1] have demonstrated that digital transformation has an impact on redistribution of activities and decision-making power among organizational levels, enhancing strategic flexibility and increasing the complexity of coordination. Moreover, AlNuaimi et al. [2] prove that the digital transformation success requires organizational agility and strategic alignment, meaning that value created by digital infrastructure can be realized only via managers' capability of translating information into actions.

Organizational learning is especially vital in this conversion process. In particular, Awad and Martín-Rojas [3] consider organizational learning to be one of the mechanisms that allow the digital transformation to

increase organizational resilience, whereas Do et al. [4] have proved that learning helps to connect resource-based management approach and resilience and innovation. Moreover, the systematic review conducted by Evenseth et al. [5] proves that organizational learning facilitates anticipation, coping, and adaptation in various phases of resilience. Finally, digital transformation impacts the essence of adaptation as well. Specifically, Browder et al. [6] have found that digital capabilities can enhance the speed, flexibility, and collaboration during disruption, whereas Khurana et al. [7] develop a concept of resilience as a higher-order dynamic capability emerged during digital-enabled organizational change.

Modern dynamic capability research pays particular attention to the fact that technology adoption is a function of firms' capability of external knowledge integration and internal resources reconfiguration [8]. Furthermore, configurational research highlights the role of digital maturity and dynamic capabilities in shaping organizational resilience [9]. Also, in the service sector, the relation between digital maturity and resilience outcomes in turbulent conditions has been established [10]. However, in prior literature, organizational learning capability, digital adaptive capability, and resilience are usually considered as separate capabilities. On the contrary, this study tests the mechanism where organizational learning capability develops the digital adaptive capability that, in its turn, affects resilience performance in conditions of technological and market uncertainties.

2. Literature review

2.1. Organizational learning capability

Organizational learning capability allows knowledge to be gained, shared, tested, interpreted and incorporated into routines. In the context of digital transformation, information produced through digital platforms, analytics and integrated workflows becomes valueless if it is not interpreted collectively. Prior research links learning with resilience and innovation demonstrating that knowledge sharing and interpretation are key to organizational adaptation in the face of environment dynamics [3, 4]. Consistent findings indicate that learning helps anticipate, cope and adapt following disruptions [5]. Knowledge gaining, knowledge sharing, experimenting and reflective learning are thus conceptualized as complementary dimensions of a higher order organizational learning capability. Taken together, these dimensions transform fragmented digital experience into organizational knowledge that can be reused.

2.2. Digital transformation and adaptive capability

Digital transformation generates vast amounts of operational information along with greater need to revise processes and reconfigure technology [1, 2]. Digital adaptive capability refers to the firm's ability to revise digital workflows, reconfigure technological assets, incorporate new information and speed up digital decision routines. Crisis management literature demonstrates that digital capabilities facilitate adaptation speed and flexibility [6], while the dynamic capabilities approach emphasizes sensing, seizing and transforming aspects of technology adoption [7, 8]. Organizational learning improves this capability by allowing firms to recognize useful information and disseminate successful changes.

2.3. Resilience performance

Resilience performance captures the actual ability of an organization to maintain critical operations, withstand disruptions, adjust its resources and return to performance following negative shocks. Recent configurational and services sector studies demonstrate that resilience depends on the combinations of digital maturity,

adaptive capability and organizational resources [9, 10]. Learning capability provides the information base for recognizing the patterns of failure, whereas digital adaptive capability transforms this information into process revision and technological responses. Thus, resilience performance is modeled as an outcome of digital adaptation enabled by learning rather than a direct result of digital investments alone.

3. Methodology

3.1. Research design and sample

The quantitative cross-sectional survey aims at 420 middle and senior managers within Chinese manufacturing and service companies. The companies should apply enterprise-wide digital transformation for at least two years via cloud computing, digital workflow, analytics platform, or data-driven management system. Participants should have no less than three years of experience and be engaged in transformations activities.

Qualtrics software is applied for questionnaires delivery. Preliminary checks verify the respondent's position, experience, industry, and involvement in transformation activity. Questionnaires having more than 10% of missing items, less than three minutes completion time or showing invariant items across the substantive items are removed. Anonymized data is exported to IBM SPSS Statistics 29 for preliminary screening and SmartPLS 4 for measurement and structural analyses. The overall research design and PLS-SEM analytical workflow are illustrated in Figure 1.

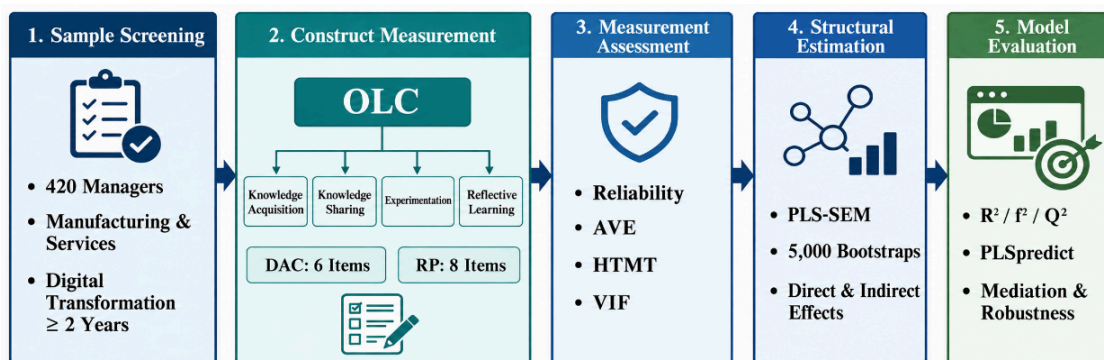


Figure 1. Research design and PLS-SEM analytical workflow

3.2. Measurement model

Seven-point Likert scale from strongly disagree to strongly agree is used for all constructs. Organizational learning capability is specified as reflective-reflective higher-order construct with four dimensions: knowledge acquisition, knowledge sharing, experimentation, and reflective learning. Four items are developed for each dimension resulting in sixteen organizational learning items. Two stages latent variable score method is employed using first-order factor scores as higher-order indicators. Digital adaptive capability is specified using six items: fast digital process adjustment, technology reconfiguration, digital resource integration, and fast response. Resilience performance is specified using eight items: operational continuity, disruption absorption, fast adaptation, resource recovery, and restoration after disruption. Control variables include firm size, firm age, industry, duration of digital transformation, and intensity of digital investment. Indicator loadings less than 0.708 can be excluded only if deletion improves composite reliability and average variance extracted while not reducing conceptual coverage.

3.3. Structural model and hypothesis testing

The structural model specifies organizational learning capability as the independent variable, digital adaptive capability as the mediator, and resilience performance as the dependent variable. The mediation mechanism is specified as shown in Equations (1) - (2):

$$DAC_i = \alpha_0 + \alpha_1 OLC_i + \sum_{k=1}^5 \gamma_k C_{ki} + \varepsilon_{1i} \quad (1)$$

$$RP_i = \beta_0 + c' OLC_i + \beta_1 DAC_i + \sum_{k=1}^5 \theta_k C_{ki} + \varepsilon_{2i} \quad (2)$$

In Equation (1), *OLC* denotes organizational learning capability, *DAC* denotes digital adaptive capability, and *RP* denotes resilience performance. C_{ki} represents the five control variables for firm *i*. α_1 captures the OLC-to-DAC effect, β_1 captures the DAC-to-RP effect, and c' represents the direct OLC-to-RP effect after accounting for the mediator. This specification separates knowledge accumulation from operational conversion.

3.4. Data analysis procedure

IBM SPSS Statistics 29 is applied to conduct descriptive statistics, missing data analysis, common method variance detection, and preliminary reliability tests. Harman's single factor test and complete collinearity VIFs detect common method variance and multicollinearity respectively.

SmartPLS 4 computes the measurement model and structural equation model using path weighting strategy, 300 iterations at most and a convergence criterion of 0.0000001. The consistency of the constructs will be analyzed using Cronbach's alpha, rho_A, and composite reliability; convergent validity will be assessed using average variance extracted while the discrimination will be checked by HTMT. Structural evaluation will provide path coefficients (standardized), R^2 , adjusted R^2 , f^2 , SRMR, and Q^2 . Statistical significance will be analyzed through 5,000 bootstrap samples and 95% confidence interval.

4. Results

4.1. Measurement model reliability and validity

The simulated 420-case dataset produced stable construct distributions. Organizational learning capability recorded Mean = 5.12 and SD = 0.86; digital adaptive capability recorded Mean = 4.94 and SD = 0.97; resilience performance recorded Mean = 5.03 and SD = 0.91. Standardized indicator loadings ranged from 0.731 to 0.892 and were significant at $p < 0.001$. Cronbach's alpha ranged from 0.881 to 0.932, composite reliability from 0.917 to 0.944, AVE from 0.612 to 0.704, HTMT from 0.593 to 0.781, and VIF from 1.42 to 2.63 (see Table 1).

Table 1. Measurement and structural model results

Construct / Path	Estimate	Reliability / Model Evidence	Bootstrap Evidence
Organizational Learning Capability	Mean = 5.12; SD = 0.86	$\alpha = 0.932^{***}$; CR = 0.944***; AVE = 0.612***	—
Digital Adaptive Capability	Mean = 4.94; SD = 0.97	$\alpha = 0.901^{***}$; CR = 0.927***; AVE = 0.679***	—

Table 1. Continued

Resilience Performance	Mean = 5.03; SD = 0.91	$\alpha = 0.914^{***}$; CR = 0.936^{***} ; AVE = 0.704^{***}	$R^2 = 0.624^{***}$; $Q^2 = 0.318^{***}$
OLC $\rightarrow$ DAC	$\beta = 0.648^{***}$	$f^2 = 0.724^{***}$	$t = 16.62$; 95% CI = [0.568, 0.719]
DAC $\rightarrow$ RP	$\beta = 0.463^{***}$	$f^2 = 0.301^{***}$	$t = 9.85$; 95% CI = [0.369, 0.550]
OLC $\rightarrow$ RP	$\beta = 0.287^{***}$	$f^2 = 0.118^{***}$	$t = 5.86$; 95% CI = [0.189, 0.381]
OLC $\rightarrow$ DAC $\rightarrow$ RP	$\beta = 0.300^{***}$	VAF = 0.511^{***}	$t = 7.89$; 95% CI = [0.229, 0.377]

Note: *** indicates statistical significance at the 0.1% level. Numerical results are simulated for manuscript development and must be replaced with empirical outputs before submission.

4.2. Effects of organizational learning capability on resilience performance

Organizational learning capability showed a significant direct effect on resilience performance, with $\beta = 0.287^{***}$ and $t = 5.86$. Its effect on digital adaptive capability was stronger, with $\beta = 0.648^{***}$ and $t = 16.62$. The resilience model achieved $R^2 = 0.624$ and adjusted $R^2 = 0.617$, while SRMR = 0.054 and $Q^2 = 0.318$, indicating satisfactory explanatory and predictive performance.

4.3. Mediating effect of digital adaptive capability

Digital adaptive capability significantly predicted resilience performance, with $\beta = 0.463^{***}$ and $t = 9.85$. The indirect effect was $\beta = 0.300^{***}$, with 95% CI = [0.229, 0.377]. VAF = 0.511 indicated partial mediation. PLSpredict generated $Q^2_{predict} = 0.286$. The manufacturing-service path difference was 0.036 with $p = 0.247$, supporting pathway stability.

5. Discussion

5.1. Resilience mechanism based on learning

The findings support a resilience mechanism based on learning whereby experience of an organization becomes valuable by translating knowledge into digital adaptation actions. The significance of the OLC-to-DAC path highlights that knowledge acquisition, exchange, experimentation, and reflection contribute to enhancing adaptability of the organization to digital changes. The direct effect further implies benefits through institutional memory and coordination. Nevertheless, the partial mediation implies that a considerable amount of learning value is translated through digital adaptation. Knowledge itself does not imply resilience. Organizations need to apply their knowledge to digital operations to reconfigure technologies, workflow, resource integration, and decision processes.

5.2. Implications for digital transformation management

As far as digital transformation management is concerned, managers should evaluate resilience in terms of the learning process instead of measuring technological investment alone. They can relate the analysis of digital incidents to a cross-departmental repository of knowledge, experiments within a short cycle, and the pre-

established authority on technology reconfiguration. All these become the means of linking organizational experience to future digital decisions. It provides no benefit for organizations to maintain large information repository or training programs when employees fail to reconfigure their workflow, integrate digital resources, and accelerate decisions.

6. Conclusion

This research relates organizational learning capability, digital adaptive capability, and resilience performance of enterprise digital transformation. Knowledge acquisition, exchange, experimentation, and reflective learning constitute a higher-order learning process whose resilience value is partially realized through digital reconfiguration of processes, technologies, and decisions. The simulation of the PLS-SEM analysis demonstrates a strong learning-to-adaptation relationship and partial mediation.

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