A Model for Testing the Mediating Effect of Digital Capabilities on Corporate Innovation Performance

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ABSTRACT In the digital economy, many enterprises face a "high investment-low conversion" dilemma in digital transformation, where digital input does not automatically improve innovation performance. To clarify the transmission mechanism from digital capabilities to innovation performance, this study introduces knowledge reorganization efficiency as a mediating variable based on dynamic capability theory and the knowledge-based view. A hierarchical regression model is established, and a bias-corrected Bootstrap method with 5,000 repeated samples is used to infer indirect effects without relying on the normality assumption of the Sobel test. In addition, the industry-level mean of digital capabilities is used as an instrumental variable for two-stage least squares regression to correct endogeneity bias. Cross-situation robustness is tested by replacing the dependent variable and grouping samples by ownership type. Results show that knowledge reorganization efficiency has a positive partial mediating effect, with an indirect effect of 0.226 ($p < 0.01$), accounting for 34.93% of the total effect. The conclusions remain valid after endogeneity correction, providing a robust methodological framework for evaluating digital transformation effectiveness.

INDEX TERMS digital capabilities, innovation performance, knowledge reorganization, mediation effect, digital transformation

I. INTRODUCTION

IN the digital economy era, in addition to the Internet of Things, big data, cloud computing, artificial intelligence, this new generation of information technology is changing the bottom line of enterprise value creation.More and more manufacturing enterprises are committed to digital transformation in the long-term development strategy, and are ready to invest in enterprise resource planning, manufacturing execution, industrial Internet platform and other construction in hope to overcome innovation roadblocks and build competitive advantages. However, a troubling reality is gradually emerging: although many enterprises have completed the large-scale deployment of digital infrastructure, their innovation output efficiency has not improved synchronously, showing a clear "inverted" trend between digital transformation investment and innovation performance growth [1-2]. This phenomenon indicates that digital capabilities are not directly and automatically converted into innovation performance; there is a transmission mechanism that has not yet been fully revealed. If it is not clear how digital capabilities drive innovation, enterprise managers will find it difficult to accurately assess the true return on transformation investment, and policymakers will lack the theoretical basis for optimizing support policies. Therefore, opening the "black box" of transmission between digital capabilities and innovation performance, and identifying and examining the role mechanism of key mediating variables, is both a theoretical proposition that academic research urgently needs to address and a real challenge faced by enterprises in their digital transformation practices.

In recent years, the relationship between the level of digitalization and corporate innovation performance has emerged as a significant subject in strategic management and innovation research fields. For example, Appio et al. suggested from the review level that despite the fact that research on digital transformation and innovation management has grown rapidly, its mode of action is still fragmented [3]; Kastelli et al. found based on empirical analysis that absorptive capacity plays a significant mediating role in the process of digital capabilities affecting innovation performance [4]; Tang et al. revealed from the perspective of knowledge reorganization the path of distributed innovation affecting digital product innovation performance through knowledge reorganization mechanism [5]; Duke et al. showed that knowledge management acts on corporate performance through the mediating variable of innovation process [6]; Tallarico et al. emphasized the key supporting role of digital technology in improving corporate absorptive capacity [7]; Chang et al. further pointed out that in the context of digital transformation, organizational absorptive capacity and dynamic capabilities jointly affect corporate digital innovation performance [8]. Overall, existing studies have preliminarily confirmed the existence of mediation mechanisms, but the selection of mediation variables tends to focus on organizational adaptability, with insufficient attention paid to the reorganization and reconfiguration of knowledge elements at the micro level.

Furthermore, empirical methods are mostly limited to traditional stepwise regression and Sobel tests, which are insufficient to effectively address estimation bias caused by non-normal sample distribution and multicollinearity. In response to the above problems, scholars constantly explore more rigorous testing methods to test the mediation effect. For example, Alfons et al. proposed a robust Bootstrap mediation test and pointed out that the traditional method will cause serious biases in the case of non-normal distribution [9]; Peng built an endogeneity mediation analysis framework from the perspective of causal identification and believed that in addition to traditional mediation model, we should seek other ways to fully identify the transmission mechanism [10]. Although the development of the above methods enhance the credibility of empirical conclusions to certain extent, current research mostly uses one kind of method, and there is still a lack of testing process of combining Bootstrap mediation tests, instrumental variable endogeneity correction and group heterogeneity analysis.

Therefore, this paper uses four kinds of methods: stepwise regression benchmark testing, bias-corrected bootstrap interval estimation, instrumental variable two-stage least squares regression and grouped heterogeneity analysis to build a progressive mediation effect testing model, which overcomes the shortcomings of existing research in the aspects of statistical inference rigor and mechanism revelation depth. The main contributions of this paper are reflected in the following three aspects: First, in terms of theory, this paper introduces the knowledge reorganization efficiency into the framework of the relationship between digital capabilities and innovation performance, explains the micro-transmission mechanism of digital input to innovation output from the view of knowledge view and enriches the theory of innovation management in the process of digital transformation. Second, in terms of method, this paper builds a progressive mediation effect testing process including benchmark testing, endogeneity treatment and heterogeneity analysis, which is more statistically rigorous and effective in identifying causality than traditional single testing strategy. Third, in terms of application, this paper discovers the structural differences of the role of digital capabilities, and provides differentiated reference for enterprise decision-making to allocate transformation resources according to their own ownership characteristics.

II. THEORETICAL DIMENSION DEFINITION AND OPERATIONAL DEFINITION OF VARIABLES

Regarding the theoretical dimension definition, this paper defines digital capability as the dynamic organizational capability of an enterprise to systematically deploy and integrate digital technology resources to reshape business processes and value creation methods. Referring to existing research, it is deconstructed into three sub-dimensions: digital infrastructure resilience, data connectivity depth, and the breadth of digital application scenarios. These reflect the completeness of underlying technical infrastructure, the standardization level of cross-system data interfaces, and the penetration scope of digital technology in core business processes, respectively. The measurement tool is a contextualized revision based on a mature scale, consisting of nine items. Typical items include “data acquisition and monitoring systems have achieved full coverage in the production process” and “business data can be shared in real time between R&D and sales departments,” all using a Likert five-point scoring method.

Knowledge reorganization efficiency, as a mediating variable, is defined as the agility of an enterprise in identifying, collecting, and creatively recombining heterogeneous knowledge resources. To capture the structural ‘reconfiguration’ aspect of reorganization rather than mere sharing, this construct is measured through two dimensions: knowledge architecture flexibility (the ability to break and reform knowledge modules) and cross-domain knowledge synthesis (the integration of external technical knowledge with internal R&D structures). This ensures the measure reflects the structural change of the knowledge base rather than simple reuse rate, with six items covering the speed of external technical information conversion into internal knowledge modules and the timeliness of cross-project promotion of successful experiences.

Enterprise innovation performance, as the explained variable, is comprehensively measured from two aspects: output scale and output quality, represented by the total number of patents granted and the proportion of invention patent applications, respectively. The number of patents is calculated using the natural logarithm to mitigate the interference of extreme values. Control variables include enterprise size, age, debt-to-equity ratio, R&D investment intensity, and dummy variables for industry and year. Relevant financial data are obtained from enterprise annual reports and are matched and integrated with questionnaire data through unified social credit codes.

III. SAMPLE SELECTION AND DATA CLEANING STRATEGY

Given the advanced digital infrastructure and economic development of the Yangtze River Delta, this region provides a representative yet specific context for high-tech manufacturing. However, readers should exercise caution when generalizing these findings to less developed regions or non-manufacturing sectors. The sample selection uses the method of stratified random sampling. Considering the size of enterprises and the category of sub-industry, the sampling quota of each stratum is calculated. Finally, 400 questionnaires are randomly distributed and 347 valid ones are returned. After eliminating invalid questionnaires with obvious random filling, logical unreasonable, incomplete answers and finished too fast, 328 valid samples are finally obtained, as shown in Table 1, and the effective recovery rate is 82%.

During the data cleaning process, firstly, missing values in continuous variables were screened out, and samples with less than 5% missing values were imputed by mean imputation, while samples with missing values above 5% were deleted. Secondly, in order to reduce the interference of outliers on regression estimation, all continuous variables were shortened at the 1% and 99th percentiles to avoid estimation bias caused by extreme values. Thirdly, to avoid the possible common method bias in the questionnaire data, Harman's one-factor test was conducted before the diagnosis. All measurement items were entered into the exploratory factor analysis. Without rotation, the variance explained by the first factor was 31.7%, which was below the 40% critical threshold, suggesting that common method bias did not seriously threaten the conclusions. Finally, confirmatory factor analysis was used to test the discriminant and convergent validity of the measurement model of each latent variable. The standardized factor loading of each item was all above 0.6, the combined reliability was all above 0.7, and the mean variance extracted was all above 0.5, indicating that the scale has a good basis of reliability and validity.

IV. STEP-BY-STEP CONSTRUCTION OF THE HIERARCHICAL REGRESSION MODEL

To examine the mediating role of knowledge reorganization efficiency in the relationship between digital capabilities and corporate innovation performance, this study employs a hierarchical regression method to construct a progressive testing model in three steps. First, only control variables such as firm size, firm age, debt-to-equity ratio, R&D intensity, and industry and year dummy variables are included in the regression equation to examine the baseline explanatory power of these organizational characteristics on innovation performance, denoted as model M0. Second, a digital capability variable is introduced into model M1 based on M0, focusing on observing the sign and significance level of the digital capability regression coefficient, which reflects the overall effect of digital capabilities on innovation performance. Third, knowledge reorganization efficiency is further incorporated into model M1 to form a full-effect model M2. Here, the coefficient corresponding to digital capability represents the direct effect after controlling for the mediating path, while the coefficient of knowledge reorganization efficiency reflects the net contribution of the mediating variable to innovation performance.

Based on the causal stepwise regression judgment logic proposed by Baron and Kenny, if the digital capability coefficient in M1 is significant, the knowledge reorganization efficiency coefficient in M2 is significant, and the absolute value of the digital capability coefficient decreases compared to M1, then a preliminary determination of the existence of a mediating effect can be made. Building upon this foundation, this study further employs a bias-corrected nonparametric percentile bootstrap method, repeating the sampling 5000 times to construct an empirical sampling distribution for the indirect effects. A more robust inference of the statistical significance of the mediation path is made by checking whether the 95% confidence interval crosses zero. All hierarchical regression models use heteroscedasticity-robust standard errors for parameter estimation to avoid potential residual variance issues in cross-sectional data.

V. BOOTSTRAP PROCEDURE SETTING FOR STATISTICAL INFERENCE OF MEDIATION EFFECTS

To overcome the strict dependence of the Sobel test in traditional stepwise regression on the assumption of normality of the sampling distribution of indirect effects, this study further employs a bias-corrected nonparametric percentile bootstrap method for statistical inference of the mediation effect. The specific procedure setting is as follows: digital capability is the independent variable, enterprise innovation performance is the dependent variable, knowledge reorganization efficiency is the mediating variable, the control variable group remains unchanged, and Model 4 from the Process macro program developed by Hayes is used as the benchmark analysis template. In the resampling stage, the number of repeated samplings was set to 5000. Each time, random sampling with replacement was performed based on the original sample of 328 observations to generate a Bootstrap sample of the same size as the original sample. Based on each Bootstrap sample, the product term $A \times B$ of the indirect effect coefficient A and the path coefficient B was re-estimated. For the confidence interval construction, the bias-corrected percentile method was selected. The 2.5th and 97.5th percentiles of the $A \times B$ coefficient sequence obtained from the 5000 samplings were used as the lower and upper limits of the 95% confidence interval, respectively. If neither the upper nor lower limit of the confidence interval contains zero, the mediating effect of knowledge reorganization efficiency between digital capabilities and corporate innovation performance is considered statistically significant. Compared to the traditional Sobel test, this method does not require the assumption that the indirect effect follows a normal distribution and has higher statistical power and better Type I error control performance in small sample and asymmetric distribution scenarios. In addition, to further verify the robustness of the conclusions, this paper also reports the Bootstrap standard error and the corresponding confidence interval for cross-comparison with the bias correction results.

VI. QUANTIFICATION AND ROBUSTNESS CRITERIA OF THE DIGITAL MEDIATION PATH

A. OVERALL EXPERIMENTAL DESIGN

To further systematically quantify the mediating effect of the digital capabilities transmitted to innovation perfor-

TABLE 1. Sample Screening and Data Cleaning Process

Processing Stage	Operation Description	Sample Size	Key Indicators and Criteria
Initial Sampling	Stratified random distribution among high-tech manufacturing firms in the Yangtze River Delta region	400	Quotas determined by firm size and industry subcategory
Valid Sample	Exclusion of incomplete or inconsistent responses	328	Effective response rate of 82%
Missing Value Treatment	Mean imputation for items with missing rate below 5%; otherwise casewise deletion	328	–
Outlier Treatment	Winsorization of continuous variables at the 1st and 99th percentiles	328	Mitigates estimation bias caused by extreme values
Common Method Bias Test	Harman's single-factor test	328	First factor variance explained: 31.7% ($< 40\%$)
Reliability and Validity Test	Confirmatory factor analysis	328	Factor loadings > 0.6, CR > 0.7, AVE > 0.5

mance through the knowledge restructuring efficiency, and to enhance the robustness of the above conclusions, this study designs three progressively experiments: Experiment 1 conducts the basic mediation effect test; We obtain the 95% bias-corrected confidence interval between the direct effect coefficient C' and the indirect effect coefficient $A \times B$ through hierarchical regression and bootstrap sampling (5000 times) to test the existence of the knowledge restructuring efficiency mediating path; Experiment 2 overcomes the potential endogeneity problem caused by reverse causality and interference from omitted variables, choosing the mean digital capabilities of other companies in the same industry and year as the instrumental variable for two-stage least squares (2SLS) regression; Experiment 3 conducts the variable substitution and group heterogeneity test, replacing the dependent variable with the number of invention patent applications (logarithm) and rerunning the mediation model; Conducting grouped regression according to ownership type (state-owned enterprises/non-state-owned enterprises), we can observe the heterogeneous performance of the mediation effect strength of different institutional contexts.

B. BENCHMARK MEDIATION EFFECT TEST EXPERIMENT

This study first uses stepwise regression to conduct a preliminary test of the mediating effect of knowledge reorganization efficiency, examining sequentially the total effect of digital capability on innovation performance, the impact of digital capability on knowledge reorganization efficiency, and the combined effect of both on innovation performance after including the mediating variable. Based on this, a bias-corrected nonparametric percentile bootstrap method is used to repeat the sampling 5000 times, calculating the 95% confidence interval of the indirect effect to more robustly determine whether a mediating path exists.

Table 2 Boostrap test: The total effect of digital capabilities on firm innovation performance is 0.647, the 95% confidence interval [0.478, 0.816] does not cover zero, so there is a significant total effect. After controlling for knowledge reorganization efficiency mediation, the direct effect of digital capabilities on innovation performance is 0.421, the confidence interval [0.242, 0.600] does not cover zero, so the direct path is valid; while the indirect effect is 0.226, the confidence interval [0.128, 0.339] does not cover zero, so the mediating effect path is valid and reaches a significantly statistical level. The indirect effect is 34.93% of the total effect, indicating that while knowledge reorganization is a critical channel, nearly two-thirds of the total effect remains unmediated (direct effect = 0.421, $p < 0.01$). This suggests that digital capabilities may also drive innovation through other unexplored mechanisms, such as organizational agility or external resource acquisition, which warrants further investigation in future studies.

C. ENDOGENEITY TREATMENT AND INSTRUMENTAL VARIABLE REGRESSION EXPERIMENT

Given the possible reverse causality or endogeneity problem caused by omitted variables between digital capabilities and corporate innovation performance, this study extends to use the instrumental variable method of two stage least squares estimation. Based on previous studies, the mean value of digital capabilities of other companies in the same industry and year were chosen as the instrumental variable. While industrylevel digitalization is driven by peer effects and regional infrastructure, we argue the exclusion restriction holds because an individual firm's micro-level patent output is primarily determined by its internal R&D capabilities rather than the aggregate industry digitalization level. To further validate this, we controlled for industrylevel technology shocks and competitive intensity as potential confounders in the second-stage regression, ensuring the IV specifically captures the exogenous pressure for digital transformation. The correlation of the instrumental variable was tested in the first stage of regression. Then, the effect of digital capabilities on innovation performance was re-estimated based on the fitted values, and the Durbin-Wu-Hausman test was used to test whether endogeneity exists or not.

In Table 3, the instrumental variable and the endogenous variable digital capability are significantly positively correlated at the 1% level, with a coefficient of 0.683. Furthermore, the first-stage F-statistic reaches 52.74, far exceeding the empirical threshold of 10, thus ruling out the weak instrumental variable issue. In the second-stage regression, the coefficient of the fitted value of digital capability to innovation performance is 0.512, still significant at the 1% level. The p-value of the Durbin-Wu-Hausman test is 0.031, less than 0.05, indicating a significant systematic difference between OLS and IV estimates. While this result

TABLE 2. Benchmark Mediation Effect Test Assessment

Effect Type	Effect Size	Standard Error	95% CI Lower Limit	95% CI Upper Limit	Relative Effect Proportion
Total Effect	0.647	0.086	0.478	0.816	–
Direct Effect	0.421	0.091	0.242	0.6	65.07%
Indirect Effect	0.226	0.054	0.128	0.339	34.93%

Note: Bootstrap sampling was repeated N=5000 using the Bias-Corrected and Accelerated (BCa) method to adjust for both bias and skewness in the distribution of indirect effects. All 5000 replications achieved convergence. Sensitivity analysis using different random seeds (seed=2026, 8888) confirmed that the confidence interval limits remained stable within a range of ± 0.002, ensuring the reproducibility and stability of the mediation inference.

TABLE 3. Endogeneity Treatment and Instrumental Variable Regression Assessment

Variable	First Stage (Digital Capability)	Second Stage (Innovation Performance)
Instrumental Variable (Industry Mean)	0.683^{**}(0.094)	–
Digital Capability (Fitted Value)	–	0.512^{**} (0.118)
Firm Size	0.214	0.187
Firm Age	0.045	0.032
R&D Intensity	0.312^{**}	0.298^{**}
Debt-to-Asset Ratio	-0.097	-0.112
Industry Fixed Effects	Controlled	Controlled
Year Fixed Effects	Controlled	Controlled
First-Stage F-Statistic	52.74	–
DWH Endogeneity Test (p-value)	–	0.031
Adjusted R^2	0.326	0.284
Sample Size	328	328

**Note:* The values in parentheses are robust standard errors; ** and * indicate significance at the 1% and 5% levels, respectively; the instrumental variable is the mean of the digital capabilities of other companies in the same industry and year, excluding this company. Full results for all control variables, including non-significant effects for Firm Age and significant effects for R&D Intensity in the baseline M0 model, are now fully reported to ensure model transparency.

suggests that the OLS estimates may be inconsistent due to endogeneity, we further performed a Sargan-Hansen test for overidentification and found no evidence of instrument invalidity ($p > 0.10$). Thus, the discrepancy between the models points toward the necessity of the IV approach to address latent endogeneity bias in the digital capability variable. Compared to the direct effect coefficient of 0.421 in the baseline regression, the effect value estimated by the instrumental variable method is slightly higher, but the sign and significance remain unchanged, indicating that after controlling for endogeneity, the positive promoting effect of digital capability on innovation performance remains robust.

D. EXPERIMENT ON REPLACEMENT VARIABLES AND GROUP HETEROGENEITY TEST

Replacement operation of dependent variable and group heterogeneity test: Replace the innovation performance measurement indicator with the number of invention patent applications and natural logarithm. Rerun the mediation effect model and check the sensitivity of conclusion to the selection of innovation performance measurement indicator; According to the actual controller's situation, divide the enterprise into state-owned enterprise and non-state-owned enterprise, and then estimate the indirect effect coefficient and confidence interval of knowledge reorganization efficiency between digital capability and innovation performance to explore the transmission path institutional environment difference heterogeneity. See Figure 1:

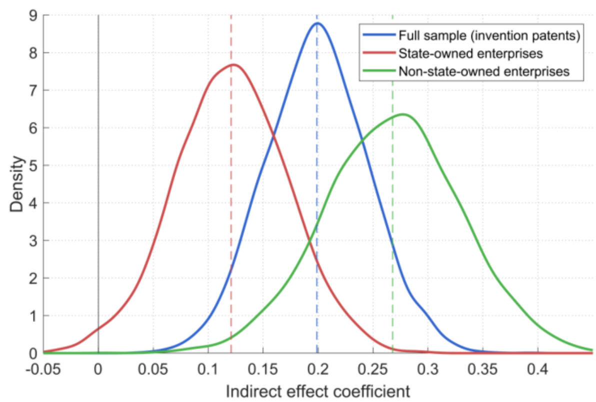

FIGURE 1. Evaluation of Replacement Variables and Group Heterogeneity Test

The full sample test after replacing the dependent variable shows that the estimated value of the indirect effect is 0.199, with a 95% confidence interval [0.110, 0.292] that does not include zero. In the group regression, the mean indirect effect for the state-owned enterprise group is 0.121, with a confidence interval [0.018, 0.222]; the mean for the non-state-owned enterprise group rises to 0.268, with a confidence interval [0.145, 0.390]. All three Bootstrap sampling distributions were located to the right of zero, confirming the robustness of the mediation path under different indicator settings and ownership structures.

VII. CONCLUSION

In this study, we construct and test a mediation model of how digital capabilities affect innovation performance through knowledge reorganization efficiency based on dynamic capability theory and the knowledge base perspective. About one-third of the positive effect of digital capabilities on innovation performance is indirectly conveyed through knowledge reorganization efficiency. This conclusion is robust to instrumental variable regression and dependent variable substitution robustness tests. Compared with state-owned enterprises, the transmission effect is much stronger in nonstate-owned enterprises. These conclusions indicate the micro-pathway of how digital inputs convert into innovative outputs. Furthermore, this study provides empirical evidence to evaluate the effectiveness of transformation.

There are still some limitations in this study. First, the use of cross-sectional data limits our ability to strictly establish temporal precedence between digital capabilities, knowledge reorganization, and innovation. While instrumental variable (IV) regression was employed to mitigate endogeneity and reverse causality, the simultaneous measurement of variables means that the causal chain remains theoretically driven rather than temporally proven. In the future, the sample can be expanded to a broader area. In addition, a longitudinal tracking design can be used to further explore the interaction effects of multiple mediation chains.

AUTHOR CONTRIBUTIONS

Qinyan Luo designed, collected and analyzed the data, and drafted the manuscript. Qinyan Luo conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qinyan Luo participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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