Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Digital technology adoption and the composition of firm innovation: Evidence from Chinese listed firms

Hui Wu
Central South University of Forestry and Technology
Xinyi Dong
Central South University of Forestry and Technology
Xinyi Du
Xinyi_Du@yeah.net

Jinan University

Article

Keywords: digital technology adoption, exploratory innovation, exploitative innovation, innovation ambidexterity, annual-report text

Posted Date: November 16th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11179008/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Digital technology adoption and the composition of firm innovation: Evidence from Chinese listed firms

Abstract. Digital technology adoption may affect whether firms explore unfamiliar technological domains or refine knowledge they already use. This study examines whether two indicators based on annual-report terminology are associated with exploratory and exploitative innovation: the frequency of terms covering six digital technology domains and the frequency of terms describing integration into four operational areas. The sample links annual-report text to patent data for 19,606 firm-year observations covering Chinese listed firms from 2011 to 2023. Fixed-effects estimates are positive for both outcomes. A one-standard-deviation increase in either adoption measure is associated more strongly with exploitative innovation; the standardised coefficients are 1.9 to 2.4 times the corresponding estimates for exploratory innovation. Digital adoption is also associated with R&D intensity, workforce composition, and productivity. For exploratory innovation, the subsample estimates show context-specific positive associations across environmental dynamism, industry factor intensity, and executives' R&D backgrounds; for exploitative innovation, both measures remain positive across the principal subsamples. Formal cross-group coefficient differences are not tested. The results describe how digital adoption relates to inventive activity in new and familiar technological domains.

Keywords: digital technology adoption; exploratory innovation; exploitative innovation; innovation ambidexterity; annual-report text

1. Introduction

Digital technologies have become general-purpose inputs into how firms collect, process, and exchange information. Data analytics, cloud computing, artificial intelligence, and related tools reduce the costs of storing, searching, and recombining knowledge (Goldfarb and Tucker 2019; Yoo et al. 2010). Their economic value also depends on complementary investments in organisation and human capital (Bresnahan et al. 2002; Bloom et al. 2012). These changes are directly relevant to innovation because digital infrastructure can alter both the search for unfamiliar knowledge and the use of knowledge already held within the firm.

Firms routinely balance exploration and exploitation. Exploratory innovation moves into technological domains that are new to the firm, whereas exploitative innovation refines its established knowledge base (March 1991; Katila and Ahuja 2002). Digital search and simulation may facilitate exploration by widening access to external information and lowering experimentation costs. Codified routines, real-time monitoring, and searchable knowledge repositories may instead provide more immediate support for exploitation. The central question is therefore whether digital technology use and its operational integration are associated differently with exploratory and exploitative innovation. This distinction matters because an increase in aggregate patenting does not reveal whether a firm is extending its technological boundaries or deepening an existing trajectory.

Research on digital transformation has examined productivity, firm value, business models, and organisational design (Brynjolfsson et al. 2021; Hanelt et al. 2021; Verhoef et al. 2021). A growing strand now addresses ambidextrous innovation directly, but its findings diverge. Xu et al. (2022) find a stronger effect on exploitation using an annual-report digitalisation index and patent-type proxies. Jiang et al. (2024) and Li and Xiong (2025) report stronger effects on exploration, whereas Li and Zhang (2025) find that digital transformation promotes exploitative innovation while suppressing exploratory innovation. These conflicting results leave two measurement questions unresolved. A composite transformation index

cannot show whether the prominence of digital technologies and their integration into business operations are related differently to exploration and exploitation. Measures based on patent type or innovation expenditure may also fail to capture whether an invention extends the focal firm's knowledge base or reuses familiar technological classes. Addressing both questions in one design permits a more precise account of how digital adoption changes the composition of firm innovation.

To examine these margins jointly, we assemble a panel of Chinese A-share listed firms from 2011 to 2023. Listed firms issued annual reports under common disclosure rules during a period of rapid digitalisation, allowing digital terminology to be measured consistently across firms and years. *DT_Scope* records the log frequency of terms covering six digital domains, and *DT_Deep* records the log frequency of terms describing digital integration into production, management, marketing, and products. Patent applications are classified relative to each firm's pre-2010 technological portfolio: a four-digit International Patent Classification (IPC) class is exploratory when absent from that portfolio and exploitative when present in it. The empirical models include firm, year, industry, and city fixed effects.

The analysis yields three main findings. First, both dimensions of digital adoption are positively associated with exploratory and exploitative innovation, but the standardised coefficients for exploitative innovation are 1.9 to 2.4 times as large as the corresponding coefficients for exploratory innovation (Table 2). This pattern suggests that digital adoption is more closely related to the refinement of established knowledge than to entry into new technological domains. Second, the organisational-resource estimates display a common pattern across research investment, workforce composition, and operating efficiency. Both adoption measures are positively associated with these resources, and each resource is positively associated with both innovation outcomes in the joint models (Table 9). These estimates provide evidence consistent with potential organisational-resource channels. Third, the exploratory subsample estimates show context-specific positive associations across environmental dynamism, industry factor intensity, and executives' R&D backgrounds. Both indicators are positively associated with exploratory innovation in high-dynamism environments; *DT_Deep* is positive in technology-intensive industries, whereas *DT_Scope* is positive in asset- and labour-intensive industries. The estimates by executives' R&D backgrounds show a similar contextual pattern. For exploitative innovation, both measures remain positive across the principal subsamples (Tables 9–12).

This study contributes to the literature in three ways. First, it helps clarify why previous studies reach different conclusions about whether digital transformation favours exploration or exploitation. Prior research reports a stronger exploitative effect (Xu et al. 2022), a stronger exploratory effect (Jiang et al. 2024; Li and Xiong 2025), or a positive exploitative effect combined with a negative exploratory effect (Li and Zhang 2025). By disaggregating digital adoption into *DT_Scope* and *DT_Deep* and formally testing the cross-outcome differences after standardisation, this study shows that both adoption dimensions are more strongly associated with exploitation. The evidence identifies an asymmetry that a single digital-transformation index cannot reveal. Second, it brings the empirical measurement of ambidextrous innovation closer to its firm-specific theoretical meaning. Several closely related studies distinguish exploration and exploitation using patent type or innovation expenditure (Xu et al. 2022; Li and Zhang 2025). We instead classify every four-digit IPC class against the focal firm's own pre-2010 patent portfolio. This benchmark captures entry into new technological domains and reuse of established knowledge rather than differences between legal patent categories. Third, it brings three organisational-resource margins into the analysis of digital adoption and ambidextrous innovation. Previous studies emphasize knowledge flow, intellectual capital, competition, risk tolerance, or industrial knowledge bases (Xu et al. 2022; Jiang et al. 2024; Li and Zhang 2025; Li and Xiong 2025). We jointly examine research investment, workforce composition, and operating efficiency and document patterns consistent with each

as a potential channel. The industry analysis further describes different within-group patterns for *DT_Scope* and *DT_Deep* across technology-, asset-, and labour-intensive industries. This framework links the content of digital adoption to organisational resources and production contexts that prior studies have not examined jointly.

The remainder of the article is organised as follows. Section 2 develops the theoretical arguments and hypotheses. Section 3 describes the sample, variables, and empirical specification. Section 4 presents the baseline estimates, analyses of endogeneity concerns, sensitivity analyses, organisational-resource results, and heterogeneity analyses. Section 5 concludes and discusses the implications and interpretive boundaries.

2. Theoretical framework and hypotheses

Exploratory and exploitative innovation rely on different uses of a firm's technological knowledge. Digital technologies expand access to information and change how firms coordinate and apply it (Yoo et al. 2010; Nambisan et al. 2017). These capabilities can support the search for unfamiliar knowledge and the refinement of established technologies.

2.1 Digital technology adoption and exploratory innovation

Exploratory innovation involves searching beyond a firm's established technological knowledge and combining unfamiliar ideas (March 1991; Katila and Ahuja 2002). By creating technological options, exploration helps firms respond when established products or capabilities lose value (Ahuja and Lampert 2001).

Digital technologies can reduce the costs of finding, comparing, and sharing information across organisational and technological boundaries (Goldfarb and Tucker 2019; Yoo et al. 2010). Access to more varied knowledge increases opportunities to identify unfamiliar technical solutions and combine them with what the firm already knows. Digital connections among research, production, and markets can also help firms evaluate these possibilities. Because inventive use of external knowledge requires the ability to recognize and assimilate it (Cohen and Levinthal 1990), these search and coordination capabilities provide a route from digital technology adoption to exploratory innovation.

Accordingly, this study proposes the following hypothesis:

Hypothesis 1a: Digital technology adoption is positively associated with exploratory innovation.

2.2 Digital technology adoption and exploitative innovation

Exploitative innovation refines and extends technologies grounded in a firm's existing knowledge (March 1991; Levinthal and March 1993). It improves established products and processes and allows firms to draw further value from accumulated technical experience.

Digital technologies make existing knowledge easier to retrieve, compare, and update. Data from ongoing operations can reveal recurring problems and enable faster feedback between technical and operational units, helping firms adapt known solutions. Repeated use of existing knowledge builds reliable routines, while process management supports the refinement of established activities (Katila and Ahuja 2002; Benner and Tushman 2003). Digital technology adoption can therefore support exploitative innovation by improving how firms use what they already know.

Accordingly, this study proposes the following hypothesis:

Hypothesis 1b: Digital technology adoption is positively associated with exploitative innovation.

2.3 Differential associations with exploratory and exploitative innovation

Digital technologies can support both forms of innovation, but translating new information into exploratory inventions requires firms to recognize, absorb, and combine unfamiliar knowledge. This process depends on related prior knowledge and experimentation (Cohen and Levinthal 1990; Katila and Ahuja 2002), and its returns tend to be uncertain and delayed (March 1991). Digital access to information may therefore take time to yield inventions beyond established technological domains.

Exploitative invention begins with problems and knowledge that firms already understand. Digital tools can be applied within established workflows, where data and feedback help refine familiar technologies more directly (Levinthal and March 1993; Benner and Tushman 2003). The gains in information processing and coordination from digital adoption are therefore likely to appear more readily in exploitative than in exploratory innovation.

Accordingly, this study proposes the following hypothesis:

Hypothesis 2: Digital technology adoption is more strongly associated with exploitative innovation than with exploratory innovation.

2.4 Potential organisational-resource channels

The innovation value of digital adoption depends in part on how firms convert information-processing capabilities into deployable organisational resources. We organize this conversion around three margins: research investment, workforce capabilities, and operating efficiency. These margins capture the resources committed to innovation, the skills used to interpret and apply knowledge, and the capacity released from routine operations.

First, digital tools reduce the costs of storing, searching, and recombining knowledge, allowing firms to deploy research resources across a wider range of projects (Goldfarb and Tucker 2019; Cohen and Levinthal 1990). Greater R&D intensity can support experimentation in unfamiliar technological fields and continued refinement within established ones. Second, digital systems increase demand for employees who can analyse data, operate technical systems, and integrate external information with firm-specific knowledge (Autor et al. 2003; Bresnahan et al. 2002). Highly educated employees strengthen the capacity to absorb unfamiliar knowledge, while technical employees help embed digital tools in established workflows.

Third, integrated production and information systems can reduce downtime, waste, and coordination costs, thereby improving total factor productivity (Syverson 2011). Higher operating efficiency creates resources for uncertain search and shortens feedback cycles in the refinement of familiar technologies. The framework therefore predicts two linked patterns: digital adoption should be positively associated with these organisational resources, and the resources should in turn be positively associated with both exploratory and exploitative innovation.

Accordingly, this study proposes the following hypothesis:

Hypothesis 3: The positive associations of digital technology adoption with exploratory and exploitative innovation are partly transmitted through higher R&D intensity, stronger workforce capabilities, and greater operating efficiency.

3. Methods

3.1 Sample and data

The sample covers Chinese A-share listed firms from 2011 to 2023. Patent classes observed before 2010 define each firm's fixed initial knowledge base, so 2010 serves as the classification cutoff and does not enter the regressions. The sample excludes firms under special treatment, financial and insurance firms, firms in abnormal operating states, and observations with missing regression variables. The resulting unbalanced panel contains 19,606 firm-year observations. Financial and patent data come from the China Stock Market and Accounting Research database, and digital technology measures are constructed from annual reports. Continuous variables are winsorized at the 1st and 99th percentiles. The estimation period begins in 2011 because the matched employee-structure data used in the analysis are available from that year.

The unit of analysis is the firm-year. Firm identifiers and years uniquely identify all observations in the estimation file. The panel covers 3,053 firms before the high-dimensional fixed-effects estimator removes singleton groups; the baseline regressions retain 2,736 firms and 19,606 observations. Annual reports are matched to stock codes and reporting years.

3.2 Measures

Exploratory and exploitative innovation are constructed from invention and utility-model patent applications. For each firm, IPC classes observed before 2010 define the initial technological knowledge base. A patent application is exploitative if its four-digit class belongs to this fixed set and exploratory if its class is absent from the set. Both annual counts are transformed using ln(1 + count). These measures capture inventive activity rather than patent quality or commercial value (Dang and Motohashi 2015).

The classification is firm specific. A technology class may be exploratory for one firm and exploitative for another, depending on their prior patent portfolios. This firm-relative benchmark captures organisational exploration and exploitation more closely than one based only on the age of a technology.

Digital technology adoption is measured from a 158-term dictionary compiled from policy documents and industry reports. Annual reports are tokenized, matched to the dictionary, and aggregated at the firm-year level. DT_Scope is ln(1 + frequency) for terms covering big data, cloud computing, artificial intelligence, blockchain, the Internet of Things, and 5G. DT_Deep is ln(1 + frequency) for terms describing integration into production, management, marketing, and products. Both measures are text-based proxies for the intensity of relevant disclosure. They do not directly verify installed systems or count distinct technologies.

Candidate terms were screened before aggregation, and terms with fewer than 10 occurrences in the corpus were excluded. The retained vocabulary was assigned to the scope and depth dictionaries and counted within each annual report, following established principles for dictionary-based text analysis (Gentzkow et al. 2019; Loughran and McDonald 2011).

The models include return on assets, sales growth, intangible-asset intensity, the accumulation of owners' equity, leverage, firm age, and asset turnover. These controls capture financial capacity, growth opportunities, accumulated knowledge assets, capital structure, organisational experience, and operating efficiency, all of which may influence both digital investment and patenting. Supplementary Table S1 summarises the variable definitions, and Table 1 reports descriptive statistics.

From Table 1, *DT_Scope* has a mean of 1.501 and a standard deviation of 1.376, while *DT_Deep* has a mean of 1.368 and a standard deviation of 1.204. Exploitative innovation has a higher mean and greater dispersion than exploratory innovation. Because the outcome dispersions differ, standardised coefficients provide the more informative cross-outcome comparison.

Table 1. Descriptive statistics

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
Exp_Innovation	19,606	1.684	1.112	0.000	4.111
Use_Innovation	19,606	3.175	1.808	0.000	7.546
DT_Scope	19,606	1.501	1.376	0.000	5.106
DT_Deep	19,606	1.368	1.204	0.000	4.564
ROA	19,606	0.030	0.069	−0.261	0.216
Growth	19,606	0.132	0.361	−0.514	2.166
Intang	19,606	0.048	0.048	0.001	0.309
Capital	19,606	0.126	0.356	−0.561	2.335
Lev	19,606	0.449	0.195	0.072	0.903
Age	19,606	3.020	0.272	2.197	3.555
Turn	19,606	0.629	0.408	0.095	2.519

3.3 Empirical strategy

The baseline model is:

$$\text{Innovation}_{i,t}=\alpha_0+\alpha_1\text{DT}_{i,t}+\boldsymbol{\beta}'\text{Controls}_{i,t}+u_i+\lambda_t+\delta_j+\gamma_c+\varepsilon_{i,t} \quad (1)$$

where i, t, j, and c index firms, years, industries, and cities. We estimate separate specifications for exploratory and exploitative innovation and enter *DT_Scope* and *DT_Deep* one at a time. Firm fixed effects absorb time-invariant firm characteristics, year fixed effects absorb common shocks, and industry and city fixed effects account for residual changes associated with industry switching and relocation. Heteroskedasticity-robust standard errors are reported. All tests are two-sided.

The estimates use within-firm changes in the digital technology adoption measures and innovation outcomes after accounting for common year shocks and the included controls. Because most firms remain in the same industry and city, firm fixed effects absorb much of the time-invariant variation associated with those classifications. The industry and city effects capture residual variation among firms that switch industries or relocate. Separate models are estimated for each adoption dimension and innovation outcome, yielding four baseline specifications.

The coefficient α_1 captures the conditional within-firm association between digital technology adoption and innovation: it is the change in the logged exploratory or exploitative innovation measure associated with a one-unit increase in *DT_Scope* or *DT_Deep*, holding the included controls and fixed effects constant.

We evaluate the potential organisational-resource channels with two linked specifications. The first regresses each resource variable on *DT_Scope* or *DT_Deep*. The second adds the same resource variable to equation (1). A pattern in which digital adoption is positively associated with the resource and the resource is positively associated with innovation in the joint model is treated as mechanism-consistent evidence. All channel models retain the baseline controls and fixed effects.

4. Results

4.1 Baseline associations

Table 2 reports the baseline estimates. Both digital indicators are positively associated with exploratory innovation: the coefficient is 0.0282 for *DT_Scope* ($p = 0.0086$) and 0.0275 for *DT_Deep* ($p = 0.0176$). The corresponding coefficients for exploitative innovation are 0.0889 and 0.1079 (both $p < 0.001$).

As shown in Table 2, a one-standard-deviation increase in *DT_Scope* is associated with increases of 0.0349 standard deviations in exploratory innovation and 0.0676 standard deviations in exploitative innovation. The corresponding estimates for *DT_Deep* are 0.0297 and 0.0718. The cross-outcome differences are 0.0328 ($p = 0.0197$) for *DT_Scope* and 0.0421 ($p = 0.0009$) for *DT_Deep*. Thus, the standardised coefficients for exploitative innovation are about 1.9 to 2.4 times the corresponding coefficients for exploratory innovation. These results support Hypotheses 1a, 1b, and 2.

Table 2. Associations between digital technology adoption and innovation

	(1)	**(2)**	**(3)**	**(4)**
Outcome Variables	*Exp_Innovation*	*Exp_Innovation*	*Use_Innovation*	*Use_Innovation*
DT_Scope	0.0282***		0.0889***	
	(0.0107)		(0.0107)	
DT_Deep		0.0275**		0.1079***
		(0.0116)		(0.0115)
standardised coefficient	0.0349	0.0297	0.0676	0.0718
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
R-squared	0.505	0.505	0.831	0.831
Observations	19,606	19,606	19,606	19,606

Note: Heteroskedasticity-robust standard errors are in parentheses. Each column reports a separate firm-year regression with the seven controls listed in Supplementary Table S1 and firm, year, industry, and city fixed effects. The standardised-coefficient row reports the standardised estimate corresponding to the focal adoption measure in each column. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

4.2 Analyses of endogeneity concerns

The baseline coefficients may be affected by reverse causality and time-varying omitted variables. We therefore report three complementary analyses: instrumental-variable diagnostics, propensity score matching, and a placebo exercise. Each addresses a different empirical concern, and the results are interpreted as sensitivity evidence rather than as definitive causal identification.

Instrumental-variable diagnostics. We construct two candidate instruments for each adoption measure, denoted by $x \in \{DT_Scope, DT_Deep\}$. The first, M_{it}, is the leave-one-out annual mean across all other sample firms, $M_{it}=(\sum_j x_{jt} - x_{it})/(N_t - 1)$. The second, $Btik_{it}$, is the product of the firm's one-period lag in adoption and its own first difference, $Btik_{it}=x_{i,t-1}\Delta x_{it}$. Table 3 reports the two-stage least-squares estimates using *Mscope* and *Btikscope* for *DT_Scope* and *Mdeep* and *Btikdeep* for *DT_Deep*. The first-stage diagnostics indicate statistical relevance: the Kleibergen–Paap rk LM statistics are 3,357.24 and 3,669.85, while the corresponding Cragg–Donald Wald F statistics are 22,262.47 and 27,966.93.

The proposed exclusion restriction relies on two maintained assumptions. First, M_{it} is constructed from the adoption choices of other sample firms, so the focal firm's current innovation does not enter the instrument directly. Other firms' adoption is expected to affect the focal firm through information spillovers, demonstration effects, and competitive pressure on its own digital adoption. Conditional on firm, year, industry, and city fixed effects and the observed controls, we assume that these external adoption choices do not independently affect the focal firm's patent output. Second, $Btik_{it}$ combines the firm's prior-period adoption with its subsequent change in adoption and captures path-dependent adjustment in digitalisation. Its proposed channel runs through the focal firm's current adoption: firms with greater prior exposure respond differently to later changes in digital technology.

As Table 3 shows, the second-stage coefficients are positive for both innovation outcomes. The coefficients on *DT_Scope* are 0.035 for exploratory innovation and 0.072 for exploitative innovation; the corresponding coefficients on DT_Deep are 0.042 and 0.094. The exploratory *DT_Scope* estimate is significant at the 5 percent level (p = 0.0104); the other three are significant at the 1 percent level. Their signs match the baseline estimates; the unstandardised coefficient magnitudes are not directly comparable across the two innovation outcomes. Together with the first-stage relevance tests and the theoretical rationale for the exclusion restriction, these estimates are consistent with the baseline pattern under the proposed instrumental-variable specification.

Table 3. Instrumental-variable diagnostics

	(1)	(2)	(3)	(4)
Outcome Variables	*Exp_Innovation*	*Exp_Innovation*	*Use_Innovation*	*Use_Innovation*
Instrumented measure	*DT_Scope*	*DT_Deep*	*DT_Scope*	*DT_Deep*
Second-stage coefficient	0.035***	0.042***	0.072***	0.094***
	(0.013)	(0.014)	(0.014)	(0.014)
Kleibergen–Paap rk LM	3,357.24	3,669.85	3,357.24	3,669.85
Cragg–Donald Wald F	22,262.47	27,966.93	22,262.47	27,966.93
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	16,117	16,117	16,117	16,117

Note: Robust standard errors are in parentheses. The candidate instrument set for *DT_Scope* contains Mscope and Btikscope; the set for *DT_Deep* contains Mdeep and Btikdeep. The Kleibergen–Paap rk LM uses heteroskedasticity-robust inference, while the Cragg–Donald Wald F is reported in its conventional i.i.d. form; the robust weak-identification counterpart is the Kleibergen–Paap Wald rk F reported in the reproduction log. The first-stage diagnostics are repeated across outcome columns because the first-stage specification is the same for a given adoption measure. ***, **, and * denote p < 0.01, p < 0.05, and p < 0.10, respectively. All tests are two-sided.

Propensity score matching. Firms are classified as high or low adopters relative to the annual industry median for each adoption measure. The seven baseline controls enter the propensity-score model, and matching uses one-to-one nearest neighbors without replacement and a caliper of 0.05. The reported balance assessment indicates that observable covariate differences are substantially smaller after matching.

Table 4 reports the matched-sample estimates. For exploratory innovation, the coefficients on *DT_Scope* and *DT_Deep* are 0.034 and 0.023, statistically significant at the 1 and 10 percent levels, respectively. For exploitative innovation, the corresponding coefficients are 0.093 and 0.101, both statistically significant at the 1 percent level. The signs and magnitudes remain close to the baseline pattern, suggesting limited sensitivity to observable differences in sample composition.

Table 4. Propensity score matching estimates

	(1)	(2)	(3)	(4)
Outcome Variables	*Exp_Innovation*	*Exp_Innovation*	*Use_Innovation*	*Use_Innovation*
DT_Scope	0.034***		0.093***	
	(0.012)		(0.012)	
DT_Deep		0.023*		0.101***
		(0.013)		(0.013)
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	16,661	16,210	16,661	16,210

Note: Robust standard errors are in parentheses. Each column reports a matched-sample regression with the baseline controls and fixed effects. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

Placebo exercise. The adoption measures are randomly reassigned across the 19,606 firm-year observations in the baseline estimation sample, and equation (1) is re-estimated 500 times for each of the four adoption-outcome combinations. Supplementary Figs. S1–S4 report the coefficient distributions and associated p-values. The placebo coefficients are centred near zero, 90.6–91.8 percent of the p-values are at least 0.10, and none of the 500 placebo estimates in any specification is as large in absolute value as its baseline counterpart. Random reassignment therefore does not reproduce the baseline pattern under the stated procedure.

4.3 Sensitivity analyses

To assess whether the baseline pattern depends on specific measurement and sample choices, we conduct four sensitivity analyses. The checks replace the digital-adoption measure, restrict the patent outcomes to invention patents, exclude centrally administered municipalities, and omit observations from 2020. Each specification retains the baseline controls and fixed effects. These analyses evaluate the stability of the conditional associations across alternative definitions and samples.

Table 5 replaces *DT_Scope* and *DT_Deep* with the manuscript's aggregate digital-transformation index, *Digital*. This check examines whether the baseline pattern depends on the original 158-term dictionary and its division into scope and depth. *Digital* is positively associated with exploratory innovation (0.412) and exploitative innovation (0.880), with both coefficients statistically significant at the 1 percent level. The two coefficients retain the positive signs seen in the baseline models.

Table 5. Alternative digital-transformation index

	(1)	(2)
Outcome Variables	*Exp_Innovation*	*Use_Innovation*
Digital	0.412***	0.880***
	(0.074)	(0.073)
Control variables	√	√
Year fixed effects	√	√
Firm fixed effects	√	√
Industry fixed effects	√	√
City fixed effects	√	√
Observations	19,606	19,606
R-squared	0.506	0.832

Note: Heteroskedasticity-robust standard errors are in parentheses. *Digital* is the aggregate digital-transformation index. *** denotes p < 0.01. All tests are two-sided.

Table 6 uses the raw counts of invention-patent applications for the two innovation outcomes, following the supplied code. This specification reduces the influence of utility-model applications, which receive less substantive examination. The *DT_Scope* coefficients are 0.282 for exploratory innovation (p = 0.018) and 14.312 for exploitative innovation (p < 0.001); the corresponding *DT_Deep* coefficients are 0.231 (p = 0.060) and 11.083 (p < 0.001). All four coefficients are positive, with the exploratory *DT_Deep* estimate significant at the 10 percent level.

Table 6. Invention-patent outcomes

	(1)	**(2)**	**(3)**	**(4)**
Outcome Variables	Exploratory invention-patent count	Exploratory invention-patent count	Exploitative invention-patent count	Exploitative invention-patent countt
DT_Scope	0.282**		14.312***	
	(0.120)		(2.482)	
DT_Deep		0.231*		11.083***
		(0.123)		(2.616)
Control variables	√	√	√	√
Year fixed effects	√	√	√	√
Firm fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	19,606	19,606	19,606	19,606
R-squared	0.309	0.309	0.755	0.755

Note: Heteroskedasticity-robust standard errors are in parentheses. The outcomes are constructed from invention-patent applications only. *** denotes $p < 0.01$. All tests are two-sided.

Table 7 excludes Beijing, Shanghai, Tianjin, and Chongqing, where digital infrastructure, innovation resources, and policy support differ from those in other cities. The reduced sample contains 15,995 observations. The *DT_Deep* coefficient for exploratory innovation remains positive at 0.022 but is estimated less precisely ($p = 0.0919$). The other coefficients, 0.029 for exploratory innovation under *DT_Scope* and 0.094 and 0.101 for exploitative innovation under *DT_Scope* and *DT_Deep*, remain close to their baseline counterparts and statistically significant at conventional levels.

Table 7. Excluding centrally administered municipalities

	(1)	**(2)**	**(3)**	**(4)**
Outcome Variables	*Exp_Innovation*	*Exp_Innovation*	*Use_Innovation*	*Use_Innovation*
DT_Scope	0.029**		0.094***	
	(0.012)		(0.012)	
DT_Deep		0.022*		0.101***
		(0.013)		(0.013)
Control variables	√	√	√	√
Year fixed effects	√	√	√	√
Firm fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	15,995	15,995	15,995	15,995
R-squared	0.496	0.495	0.823	0.823

Note: Heteroskedasticity-robust standard errors are in parentheses. Beijing, Shanghai, Tianjin, and Chongqing are excluded. ***, **, and * denote p < 0.01, p < 0.05, and p < 0.10, respectively. All tests are two-sided.

Table 8 removes observations from 2020 to limit the influence of pandemic-related disruptions to production, investment, and digitalisation. The remaining sample contains 17,535 observations. The coefficients are 0.028 and 0.028 for exploratory innovation under *DT_Scope* and *DT_Deep* and 0.093 and 0.111 for exploitative innovation. All four remain positive and statistically significant, with magnitudes close to the baseline estimates.

Table 8. Excluding observations from 2020

	(1)	(2)	(3)	(4)
Outcome Variables	*Exp_Innovation*	*Exp_Innovation*	*Use_Innovation*	*Use_Innovation*
DT_Scope	0.028**		0.093***	
	(0.011)		(0.011)	
DT_Deep		0.028**		0.111***
		(0.012)		(0.012)
Control variables	√	√	√	√
Year fixed effects	√	√	√	√
Firm fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	17,535	17,535	17,535	17,535
R-squared	0.515	0.515	0.829	0.829

Note: Heteroskedasticity-robust standard errors are in parentheses. Observations from 2020 are excluded. ***, **, and * denote p < 0.01, p < 0.05, and p < 0.10, respectively. All tests are two-sided.

4.4 Evidence on potential organisational-resource channels

This section tests Hypothesis 3 by examining research investment, workforce capabilities, and operating efficiency as three potential organisational-resource channels. Table 9 reports the results.

Research investment. Digital tools reduce the costs of storing, retrieving, and recombining technical knowledge, which may allow firms to devote a larger share of revenue to research and allocate research budgets across a wider range of projects. Higher R&D intensity can support experimentation in unfamiliar technological domains as well as continued refinement along established trajectories. Following Ji et al. (2023), research investment is measured by R&D expenditure divided by operating revenue (*RD*). Columns (1) and (4) of Panel A in Table 9 show that *DT_Scope* and *DT_Deep* are positively associated with R&D intensity, with coefficients of 0.1264 and 0.1126, respectively; both estimates are significant at the 1 percent level. Columns (2), (3), (5), and (6) show that R&D intensity is positively associated with exploratory innovation (0.0165 and 0.0166) and exploitative innovation (0.0344 and 0.0345), with all four estimates significant at the 1 percent level. These linked associations are consistent with a research-investment channel.

Workforce capabilities. Digital technologies increase firms' demand for employees who can analyse data, operate technical systems, and integrate external information with firm-specific knowledge. Employees with more education can strengthen the absorption and interpretation of unfamiliar knowledge, while technical employees help embed digital tools in R&D and established operating routines. Following Xie and Guo (2022), workforce capabilities are measured by the share of employees with a bachelor's degree or above (*Talent*) and the share engaged in technical work (*Tech*).

Panel B of Table 9 reports the results for educational attainment. Columns (1) and (4) show that *DT_Scope* and *DT_Deep* are positively associated with *Talent*, with coefficients of 0.7593 and 0.6340, respectively. Columns (2), (3), (5), and (6) show that *Talent* is positively associated with exploratory innovation, with coefficients of 0.0036 in both specifications, and with exploitative innovation, with coefficients of 0.0070 in both specifications. All six estimates are significant at the 1 percent level. These results are consistent with the educational-attainment dimension of the workforce-capability channel.

Panel C of Table 9 reports the results for technical employment. Columns (1) and (4) show that *DT_Scope* and *DT_Deep* are positively associated with *Tech*, with coefficients of 0.4741 and 0.6225. Columns (2), (3), (5), and (6) show that *Tech* is positively associated with exploratory innovation, with coefficients of 0.0033 in both specifications, and with exploitative innovation, with coefficients of 0.0042 and 0.0041. These six estimates are also significant at the 1 percent level. The parallel evidence from *Talent* and *Tech* suggests that educational attainment and technical employment capture complementary dimensions of workforce capabilities.

Operating efficiency. Integrated production and information systems can improve planning and process control, reduce downtime and waste, and release human, material, and financial resources from routine operations. These resources can support experimentation with unfamiliar technologies and the refinement of established technological trajectories. Following Olley and Pakes (1996) and Yasar et al. (2008), operating efficiency is measured by total factor productivity (*TFP*) estimated with the Olley-Pakes procedure. Columns (1) and (4) of Panel D in Table 9 show that *DT_Scope* and *DT_Deep* are positively associated with *TFP*, with coefficients of 0.0409 and 0.0359, respectively; both estimates are significant at the 1 percent level. Columns (2), (3), (5), and (6) show that *TFP* is positively associated with exploratory innovation, with coefficients of 0.2280 and 0.2292, and with exploitative innovation, with coefficients of 0.4592 and 0.4591. All four *TFP* estimates are significant at the 1 percent level. These linked associations are consistent with an operating-efficiency channel.

Across the four resource measures, digital technology adoption is positively associated with research investment, workforce capabilities, and operating efficiency, and each resource measure is positively associated with both innovation outcomes in the joint models. The linked results are consistent with Hypothesis 3 at the level of mechanism-consistent associations.

Table 9. Evidence on potential organisational-resource channels

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Variables	*Resource proxy*	*Exp_Innovation*	*Use_Innovation*	*Resource proxy*	*Exp_Innovation*	*Use_Innovation*
Panel A. Research investment: RD						
DT_Scope	0.1264***	0.0261**	0.0845***			
	(0.0234)	(0.0107)	(0.0107)			
RD		0.0165***	0.0344***		0.0166***	0.0345***
		(0.0042)	(0.0047)		(0.0042)	(0.0047)
DT_Deep				0.1126***	0.0256**	0.1040***
				(0.0242)	(0.0116)	(0.0114)
Panel B. Workforce capabilities: Talent						
DT_Scope	0.7593***	0.0255**	0.0836***			
	(0.0975)	(0.0107)	(0.0107)			
Talent		0.0036***	0.0070***		0.0036***	0.0070***
		(0.0011)	(0.0012)		(0.0011)	(0.0012)

	(1)	(2)	(3)	(4)	(5)	(6)
DT_Deep				0.6340***	0.0252**	0.1034***
				(0.0961)	(0.0116)	(0.0115)
Panel C. Workforce capabilities: Tech						
DT_Scope	0.4741***	0.0266**	0.0869***			
	(0.0920)	(0.0107)	(0.0107)			
Tech		0.0033***	0.0042***		0.0033***	0.0041***
		(0.0011)	(0.0012)		(0.0011)	(0.0012)
DT_Deep				0.6225***	0.0255**	0.1054***
				(0.0969)	(0.0116)	(0.0115)
Panel D. Operating efficiency: TFP						
DT_Scope	0.0409***	0.0189*	0.0701***			
	(0.0033)	(0.0108)	(0.0106)			
TFP		0.2280***	0.4592***		0.2292***	0.4591***
		(0.0307)	(0.0329)		(0.0306)	(0.0328)
DT_Deep				0.0359***	0.0193*	0.0914***
				(0.0035)	(0.0116)	(0.0113)
Control variables	√	√	√	√	√	√
Firm fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Industry fixed effects	√	√	√	√	√	√
City fixed effects	√	√	√	√	√	√

Note: Columns (1) and (4) regress each panel's resource proxy on the indicated adoption measure. Columns (2), (3), (5), and (6) jointly include the resource proxy and the indicated adoption measure in the innovation model. Heteroskedasticity-robust standard errors are in parentheses. All models include the baseline controls and fixed effects. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

4.5 Heterogeneity analysis

We examine heterogeneity along three dimensions: environmental dynamism, industry factor intensity, and executives' R&D backgrounds. For each dimension, the sample is partitioned and the baseline specification is re-estimated within each subsample.

Environmental dynamism. Volatile markets increase the value of rapid search, experimentation, and knowledge recombination. Digital tools can support these activities by improving information acquisition, simulation, and coordination. Environmental dynamism is measured using the industry-adjusted variability of abnormal sales over a five-year window, scaled by average sales, and the sample is split at the median. Table 10 shows that *DT_Scope* and *DT_Deep* are positively associated with exploratory innovation in the high-dynamism subsample, with coefficients of 0.045 and 0.052, both significant at the 1 percent level. The corresponding estimates in the low-dynamism subsample are smaller and statistically indistinguishable from zero. For exploitative innovation, both adoption measures remain positive and significant in the high- and low-dynamism subsamples. The exploratory estimates are consistent with the following mechanism. When market demand and technological trajectories change rapidly, firms need to search for new knowledge, experiment with new technological combinations, and adjust their R&D direction more frequently. *DT_Scope* broadens the range of digital technologies available for these activities, while *DT_Deep* embeds digital tools more deeply in R&D and operations. In more stable

environments, firms can rely more heavily on refining existing knowledge and processes, which may weaken the association between digital adoption and exploration.

Table 10. Associations by environmental dynamism

Panel A. Exploratory innovation	**(1)**	**(2)**	**(3)**	**(4)**
Environmental dynamism	High	Low	High	Low
DT_Scope	0.045***	0.015		
	(0.017)	(0.015)		
DT_Deep			0.052***	0.016
			(0.019)	(0.016)
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	9,543	9,720	9,543	9,720
R-squared	0.503	0.538	0.503	0.538
Panel B. Exploitative innovation	(1)	(2)	(3)	(4)
Environmental dynamism	High	Low	High	Low
DT_Scope	0.094***	0.064***		
	(0.017)	(0.014)		
DT_Deep			0.132***	0.063***
			(0.018)	(0.015)
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	9,543	9,720	9,543	9,720
R-squared	0.792	0.862	0.793	0.862

Note: Columns (1) and (2) report separate regressions for *DT_Scope*, and columns (3) and (4) report separate regressions for *DT_Deep*. Heteroskedasticity-robust standard errors are in parentheses. All models include the baseline controls and fixed effects. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

Industry factor intensity. Production structures shape how firms can use the two dimensions of digital adoption. Technology-intensive firms face specialised design and development problems for which deeper integration into core R&D and production processes may be especially relevant. Asset-intensive firms coordinate fixed capacity, equipment, and suppliers, while labour-intensive firms coordinate heterogeneous tasks and broad product markets; broader coverage of digital technologies may support these coordination demands. Table 11 reports the corresponding estimates. For exploratory innovation, *DT_Deep* is positively associated with the outcome in technology-intensive firms (0.0357, $p = 0.0329$), while *DT_Scope* is positively associated with the outcome in asset-intensive firms (0.0610, $p = 0.0176$) and labour-intensive firms (0.0650, $p = 0.0010$). For exploitative innovation, both adoption measures are positive in every industry group, with coefficients ranging from 0.0649 to 0.1094 and $p < 0.001$ throughout. The estimates suggest that the adoption dimension associated with exploration varies across production contexts, while both dimensions are associated with exploitation across all three groups.

Table 11. Associations by industry factor intensity

Panel A. Exploratory innovation					
(1)	(2)	(3)	(4)	(5)	(6)

Industry group	Technology-intensive	Asset-intensive	labour-intensive	Technology-intensive	Asset-intensive	labour-intensive
DT_Scope	0.0088	0.0610**	0.0650***			
	(0.0153)	(0.0257)	(0.0197)			
DT_Deep				0.0357**	0.0217	0.0330
				(0.0167)	(0.0272)	(0.0212)
Control variables	√	√	√	√	√	√
Firm fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Industry fixed effects	√	√	√	√	√	√
City fixed effects	√	√	√	√	√	√
Observations	9,588	3,614	6,199	9,588	3,614	6,199
R-squared	0.497	0.501	0.532	0.498	0.500	0.531
Panel B. Exploitative innovation						
	(1)	(2)	(3)	(4)	(5)	(6)
Industry group	Technology-intensive	Asset-intensive	labour-intensive	Technology-intensive	Asset-intensive	labour-intensive
DT_Scope	0.0649***	0.1085***	0.1034***			
	(0.0149)	(0.0264)	(0.0191)			
DT_Deep				0.1075***	0.1094***	0.1001***
				(0.0160)	(0.0283)	(0.0211)
Control variables	√	√	√	√	√	√
Firm fixed effects	√	√	√	√	√	√
Year fixed effects	√	√	√	√	√	√
Industry fixed effects	√	√	√	√	√	√
City fixed effects	√	√	√	√	√	√
Observations	9,588	3,614	6,199	9,588	3,614	6,199
R-squared	0.832	0.805	0.831	0.833	0.805	0.831

Note: Columns (1) to (3) report separate regressions for *DT_Scope*, and columns (4) to (6) report separate regressions for *DT_Deep*. Heteroskedasticity-robust standard errors are in parentheses. All models include the baseline controls and fixed effects. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

Executives' R&D backgrounds. Managerial experience may shape how firms convert digital adoption into innovation. Broader digital coverage can extend external knowledge search and cross-boundary information flows. When an executive team lacks R&D experience, *DT_Scope* may supplement its limited internal technical knowledge. Deeper digital integration reaches core R&D and production processes. Executives with R&D experience may be better able to evaluate the technical value of specialised projects, allocate research resources, and direct their implementation. A firm is classified as having an executive team with an R&D background when at least one executive has such experience in a given year. Table 12 reports that *DT_Scope* is positively associated with exploratory innovation among firms without an R&D-background executive (0.036, significant at the 5 percent level), while *DT_Deep* is positively associated with exploratory innovation among firms with such an executive (0.044, significant at the 5 percent level). For exploitative innovation, both measures are positive and significant in both subsamples. The exploratory estimates are consistent with the proposed relationship between the two dimensions of digital adoption and executives' technical experience.

Table 12. Associations by executives' R&D backgrounds

Panel A. Exploratory innovation	**(1)**	**(2)**	**(3)**	**(4)**
Executive R&D background	With	Without	With	Without

DT_Scope	0.004	0.036***		
	(0.019)	(0.014)		
DT_Deep			0.044**	0.012
			(0.020)	(0.015)
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	7,117	12,132	7,117	12,132
Adjusted R^2	0.553	0.519	0.553	0.519
Panel B. Exploitative innovation	(1)	(2)	(3)	(4)
Executive R&D background	With	Without	With	Without
DT_Scope	0.067***	0.101***		
	(0.018)	(0.014)		
DT_Deep			0.099***	0.105***
			(0.020)	(0.015)
Control variables	√	√	√	√
Firm fixed effects	√	√	√	√
Year fixed effects	√	√	√	√
Industry fixed effects	√	√	√	√
City fixed effects	√	√	√	√
Observations	7,117	12,132	7,117	12,132
Adjusted R^2	0.849	0.844	0.850	0.844

Note: Columns (1) and (2) report separate regressions for *DT_Scope*, and columns (3) and (4) report separate regressions for *DT_Deep*. Heteroskedasticity-robust standard errors are in parentheses. All models include the baseline controls and fixed effects. ***, **, and * denote $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. All tests are two-sided.

5. Conclusion

5.1 Research conclusions

Using 19,606 firm-year observations for Chinese A-share listed firms from 2011 to 2023, this study examines how the scope and depth of digital technology adoption are associated with firm-specific exploratory and exploitative innovation. Three main conclusions emerge.

First, *DT_Scope* and *DT_Deep* are positively associated with both exploratory and exploitative innovation (Table 2). A one-standard-deviation increase in *DT_Scope* is associated with increases of 0.0349 standard deviations in exploratory innovation and 0.0676 standard deviations in exploitative innovation. The corresponding estimates for *DT_Deep* are 0.0297 and 0.0718. The exploitative coefficients are therefore about 1.9 to 2.4 times the corresponding exploratory coefficients. Both dimensions of digital adoption are related to innovation, with consistently larger standardised associations for the refinement and reuse of knowledge already held by the firm.

Second, digital technology adoption covaries positively with research investment, workforce capabilities, and operating efficiency. In the joint models, R&D intensity, the shares of highly educated and technical employees, and total factor productivity are each positively associated with both innovation outcomes (Table 9). These linked estimates are consistent with organisational-resource channels through which digital adoption and innovation may be connected.

Third, the subsample results indicate that the within-group associations with exploratory innovation show context-specific patterns across firm and industry categories. Both digital indicators are positively associated with exploration in more dynamic environments. *DT_Deep* is positively associated with exploration among technology-intensive firms, while *DT_Scope* is positively associated with exploration among asset- and labour-intensive firms. The estimates by executives' R&D backgrounds show a similar contextual pattern. Exploitative associations remain positive across the principal subsamples (Tables 9–12).

5.2 Policy implications

At the firm level, digital investment should be aligned with the intended innovation objective. Systems that strengthen monitoring, codification, and process integration are more closely aligned with exploitative innovation. Efforts to promote exploration should combine digital adoption with R&D capacity, technical personnel, and managerial capabilities, while the choice between broader coverage and deeper integration should reflect the firm's production and technological context.

Public programmes that support enterprise digitalisation can differentiate assistance according to industry characteristics and firms' capability bases. Technology-intensive firms may require support for integrating digital tools into R&D and production, while asset- and labour-intensive firms may place greater value on broader digital coverage for equipment, supply-chain, and task coordination. Programmes intended to strengthen exploratory innovation can also coordinate digitalisation support with technical training and R&D capacity building.

References

Ahuja G, Lampert C M (2001) Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. Strategic Management Journal 22(6-7):521–543.

Autor D H, Levy F, Murnane R J (2003) The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics 118(4):1279–1333.

Benner M, Tushman M (2003) Exploitation, exploration, and process management: The productivity dilemma revisited. Academy of Management Review 28(2):238–256.

Bloom N, Sadun R, Van Reenen J (2012) Americans do IT better: US multinationals and the productivity miracle. American Economic Review 102(1):167–201.

Bresnahan T F, Brynjolfsson E, Hitt L M (2002) Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. Quarterly Journal of Economics 117(1):339–376.

Brynjolfsson E, Rock D, Syverson C (2021) The productivity J-curve: How intangibles complement general purpose technologies. American Economic Journal: Macroeconomics 13(1):333–372.

Cohen W M, Levinthal D A (1990) Absorptive capacity: A new perspective on learning and innovation. Administrative Science Quarterly 35(1):128–152.

Dang J, Motohashi K (2015) Patent statistics: A good indicator for innovation in China? Patent subsidy program impacts on patent quality. China Economic Review 35:137–155.

Gentzkow M, Kelly B, Taddy M (2019) Text as data. Journal of Economic Literature 57(3):535–574.

Goldfarb A, Tucker C (2019) Digital economics. Journal of Economic Literature 57(1):3–43.

Hanelt A, Bohnsack R, Marz D, et al (2021) A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. Journal of Management Studies 58(5):1159–1197.

Ji Y, Zhou X, Zhang Q (2023) Digital Transformation and Enterprise Innovation: An Analysis from the Perspectives of R&D Investment and R&D Efficiency. Journal of Financial Research (4):111–129.

Jiang Y, He C, Ma W (2024) The impact of digital transformation on enterprise ambidextrous innovation: Evidence from manufacturing listed companies in China. Journal of Information & Knowledge Management 23(6):2450092. https://doi.org/10.1142/S0219649224500928

Katila R, Ahuja G (2002) Something old, something new: A longitudinal study of search behavior and new product introduction. Academy of Management Journal 45(6):1183–1193.

Levinthal D A, March J G (1993) The myopia of learning. Strategic Management Journal 14(S2):95–112.

Li F, Zhang N (2025) Digital transformation, innovation investment and quality. Finance Research Letters 75:106901. https://doi.org/10.1016/j.frl.2025.106901

Li T, Xiong S (2025) The differential impact of enterprise digital transformation on ambidextrous innovation: Evidence from China. International Review of Economics & Finance 103:104436. https://doi.org/10.1016/j.iref.2025.104436

Loughran T, McDonald B (2011) When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. Journal of Finance 66(1):35–65.

March J G (1991) Exploration and exploitation in organizational learning. Organization Science 2(1):71–87.

Nambisan S, Lyytinen K, Majchrzak A, et al (2017) Digital innovation management: Reinventing innovation management research in a digital world. MIS Quarterly 41(1):223–238.

Olley G, Pakes A (1996) The dynamics of productivity in the telecommunications equipment industry. Econometrica 64(6):1263–1297.

Syverson C (2011) What determines productivity? Journal of Economic Literature 49(2):326–365.

Verhoef P C, Broekhuizen T, Bart Y, et al (2021) Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research 122:889–901.

Xie Q, Guo Y (2022) Digital technology, innovation factor structure optimization, and firms' total factor productivity. Journal of Beijing Normal University (Social Sciences) (6):134–144.

Xu Q, Liu H, Chen Y, Tian K (2022) Understanding cognitive differences in the effect of digitalization on ambidextrous innovation: Moderating role of industrial knowledge base. Frontiers in Psychology 13:983844. https://doi.org/10.3389/fpsyg.2022.983844

Yasar M, Raciborski R, Poi B P (2008) Production function estimation in Stata using the Olley and Pakes method. The Stata Journal 8(2):221–231.

Yoo Y, Henfridsson O, Lyytinen K (2010) The new organizing logic of digital innovation: An agenda for information systems research. Information Systems Research 21(4):724–735.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- 04SupplementaryInformation.docx