Digital Technology Uncertainty Exposure and Innovation Ambidexterity: Evidence from Chinese Listed Firms

Wei Zhang[1], Jingru Chen[1], Hao Li[2], Xin Liu[3, *]

[1] School of Business Administration, Northeastern University, Shenyang, 110819, China
[2] Institute of Digital Economy Research, Northeastern University, Shenyang, 110819, China
[3] School of Economics and Management, Dalian University of Technology, Dalian, 116024, China
[*] Corresponding Author. Email: xinliu@dlut.edu.cn

Abstract

This study investigates the impact of digital technology uncertainty exposure (DTUE) on corporate innovation ambidexterity among Chinese A-share listed firms from 2012 to 2023. Distinguishing between exploratory and exploitative innovation, we construct a firm-level DTUE indicator through sentiment analysis of Management Discussion and Analysis (MD&A) sections using a DeepSeek-V3 and FinBERT hybrid Large Language Model (LLM) pipeline. Drawing on threat-rigidity theory, upper echelons theory, and the attention-based view (ABV), we theorize that DTUE suppresses exploratory innovation through managerial cognitive conservatism and R&D resource diversion channels, while leaving exploitative innovation largely unaffected. Baseline panel regressions with two-way fixed effects show that a one-standard-deviation increase in DTUE reduces exploratory innovation by approximately 1.8% and innovation ambidexterity by approximately 2.4%. These effects are confirmed via propensity score matching (PSM), COVID-year exclusion tests, and sub-dimensional analyses. Using the staggered adoption of Digital Technology Compliance Governance Standards (DTCGS) across Chinese cities as a quasi-natural experiment, multi-period difference-in-differences (DID) estimates confirm that effective digital governance restores exploratory innovation capacity. Mechanism tests validate both the managerial conservatism (psychological) and R&D diversion (resource) channels. Heterogeneity analyses reveal that the suppressive effect is particularly pronounced in non-state-owned enterprises (non-SOEs), competitive industries, and technology-intensive sectors. These findings advance the understanding of digital risk governance and its implications for innovation strategy.

Keywords: digital technology uncertainty; innovation ambidexterity; exploratory innovation; LLMs

Article History:
Received December 12, 2025
Revised February 26, 2026
Accepted March 18, 2026
Available Online March 30, 2026

ISSN: 3067-7491 See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2026.040101

Digital Technology Uncertainty Exposure and Innovation Ambidexterity: Evidence from Chinese Listed Firms

1. Introduction

The digital revolution has fundamentally transformed the competitive landscape of global business. Digital technologies—including artificial intelligence (AI), blockchain, big data analytics, Internet of Things (IoT), and cloud computing—have become indispensable enablers of productivity, service innovation, and competitive advantage (Brynjolfsson & McAfee, 2014; Nambisan et al., 2019). However, alongside these transformative opportunities, the rapid pace of digital innovation has introduced new forms of organizational uncertainty that carry material consequences for corporate strategy and resource allocation (Acemoglu & Restrepo, 2020; Lu et al., 2025). Data breaches, system vulnerabilities, algorithmic failures, and evolving cyber threats constitute what we define as digital technology uncertainty exposure (DTUE)—the degree to which a firm perceives and communicates salient digital technology risks in its operational and strategic discourse.

Innovation ambidexterity—the organizational capacity to simultaneously pursue both exploratory innovation (developing radical new technologies and knowledge) and exploitative innovation (refining and extending existing technological capabilities)—is widely recognized as a critical determinant of firm survival and long-run competitive advantage (March, 1991; Benner & Tushman, 2003; Raisch & Birkinshaw, 2008). The ambidexterity framework distinguishes between the inherently different resource profiles, managerial attention requirements, and organizational processes associated with exploration versus exploitation (O'Reilly & Tushman, 2004, 2013; Jansen et al., 2006). While both dimensions matter for organizational performance, exploratory innovation is particularly vulnerable to contextual disruptions given its longer time horizons, higher resource demands, and greater outcome uncertainty.

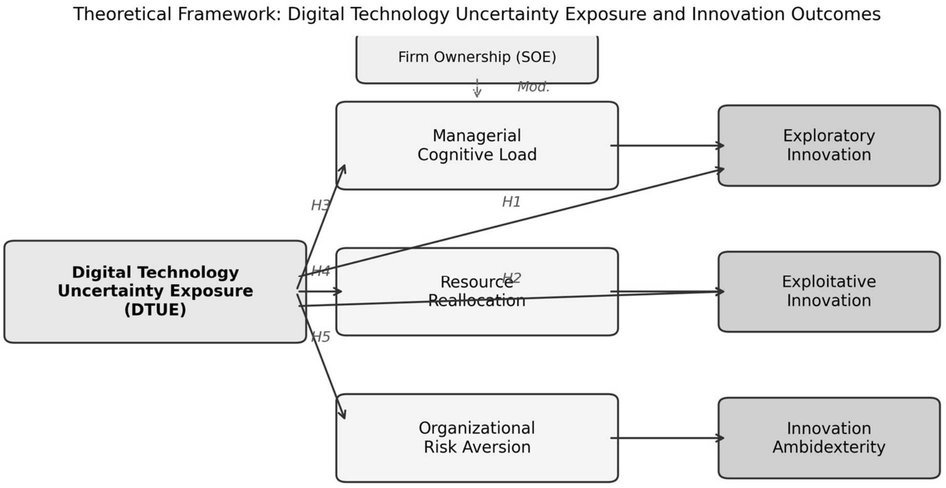

Figure 1. Theoretical Framework: Digital Technology Uncertainty Exposure and Innovation Ambidexterity

ISSN: 3067-7491 © 2026 INATGI (Institute of Advanced Technology and Green Innovation). Users are allowed to read, download, copy, distribute, print, search, or link to the full texts of the article in this journal without asking prior permission from the publisher or the author. See: https://inatgi.in/index.php/jbgi/index for more information. https://doi.org/10.63646/jbgi.2026.040101

Despite the growing scholarly attention to both digital technology adoption and corporate innovation, the intersection of digital technology risk and innovation ambidexterity remains underexplored. Existing literature predominantly examines the enabling role of digital transformation—how digitalization enhances information processing, coordination, and knowledge creation (Yang et al., 2024; Li & Zhang, 2025). The dark side of digital technology—specifically, how uncertainty and risk exposure at the firm level shape managerial behavior and innovation investment—has received comparatively limited systematic attention (Pan et al., 2022; Lu et al., 2025). This gap is consequential because DTUE constitutes a chronic, escalating, and strategically significant environmental pressure for firms across all industries.

The present study addresses this gap through four contributions. First, we construct a novel firm-level DTUE measure leveraging a DeepSeek-V3 and FinBERT LLM-based pipeline applied to MD&A disclosures of 31,248 firm-year observations from 2012 to 2023. Second, we develop a unified theoretical model integrating threat-rigidity theory (Staw et al., 1981), upper echelons theory (Hambrick & Mason, 1984), and the attention-based view (ABV; Ocasio, 1997) to generate testable predictions about the asymmetric effects of DTUE on exploration versus exploitation. Third, we provide causal identification via the staggered city-level adoption of Digital Technology Compliance Governance Standards (DTCGS) as an exogenous shock, enabling multi-period DID estimation. Fourth, through systematic heterogeneity analyses across ownership types, industry competition intensity, and technological intensity, we delineate the boundary conditions under which DTUE most acutely constrains innovation ambidexterity.

Our empirical analysis yields four key findings. First, DTUE significantly suppresses exploratory innovation ($\beta = -0.044$, $p < 0.01$) and ambidexterity ($\beta = -0.067$, $p < 0.05$) but leaves exploitative innovation statistically unaffected. Second, DID estimates confirm that effective digital governance—captured by city-level DTCGS adoption—significantly promotes exploratory innovation and ambidexterity. Third, mechanism tests validate dual channels: (a) managerial cognitive conservatism, measured by risk-averse investment behavior, and (b) R&D diversion, measured by the shift of digital investment from innovation to cybersecurity defense. Fourth, the suppressive effect is heterogeneous, being more pronounced in non-SOEs, competitive industries, and technology-intensive firms. The remainder of this paper is organized as follows. Section 2 presents the theoretical background and hypotheses. Section 3 describes data and methodology. Section 4 reports empirical results. Section 5 presents mechanism tests and heterogeneity analyses. Section 6 concludes.

2. Theoretical Background and Hypotheses

2.1 Digital Technology Uncertainty Exposure: A Threat-Rigidity Perspective

Threat-rigidity theory (Staw et al., 1981; Weick, 1988) predicts that when organizations perceive environmental threats, they respond by restricting information processing, tightening resource allocation, and reverting to established behavioral patterns. Digital technology risks—including data breaches, cybersecurity incidents, algorithmic failures, and system disruptions—constitute precisely this form of salient organizational threat (Faraj et al., 2018; Glikson & Woolley, 2020). Consistent with the threat-rigidity mechanism, firms facing elevated DTUE are expected to narrow their strategic aperture, concentrate resources on immediate operational continuity, and exhibit heightened aversion to high-uncertainty strategic commitments.

The resource-based view (RBV; Barney, 1991, 2021; Ceric et al., 2016) provides a complementary mechanism. Digital technology risks impose direct resource costs through cybersecurity infrastructure investment, incident remediation expenditures, and managerial time devoted to risk containment. These expenditures constitute a form of resource drain that competes directly with innovation investment (Nambisan et al., 2019). Dynamic capabilities theory (Teece et al., 1997; Helfat & Peteraf, 2009) further suggests that effective resource reallocation in response to environmental threats is itself a capability that must be developed over time, and that in the short run, resource diversion toward defense systematically crowds out offense.

2.2 Asymmetric Effects on Exploration vs. Exploitation

March (1991)'s foundational distinction between exploration and exploitation identifies key differences in resource requirements, time horizons, and outcome certainty. Exploitative innovation—incremental improvements to existing products, processes, and technologies—is characterized by clearer cause-effect relationships, more predictable returns, and lower resource intensity per unit of output (Benner & Tushman, 2003; Gupta et al., 2006). Exploratory innovation, by contrast, requires venturing into uncertain technological territory, sustaining long-horizon R&D commitments, and tolerating a high probability of near-term failure. From an evolutionary perspective, exploitative innovation benefits from increasing returns to scale (Arthur, 1989), meaning that even under resource pressure, firms tend to deepen their existing technological trajectories rather than abandoning them.

Under conditions of DTUE, we therefore expect an asymmetric pattern: exploratory innovation, which is most resource-intensive and outcome-uncertain, will be disproportionately suppressed, while exploitative innovation, which is more defensive and path-dependent, will be comparatively shielded. This prediction is consistent with Dunlap-Hinkler et al. (2010)'s dual innovation framework and with empirical evidence that environmental pressures tend to differentially affect exploration versus exploitation (Ozer & Zhang, 2015; Mueller et al., 2013).

H1: *DTUE is negatively associated with exploratory innovation.*

H2: *DTUE has no significant negative effect on exploitative innovation.*

2.3 Psychological Mechanism: Managerial Cognitive Conservatism

Upper echelons theory (Hambrick & Mason, 1984; Hambrick, 2007) posits that strategic choices reflect the cognitive frames, values, and risk preferences of top management teams. Behavioral agency theory (Wiseman & Gomez-Mejia, 1998) predicts that when executives face threats to organizational survival or personal performance evaluations, they shift toward loss aversion and risk-minimizing behavior. Digital technology risks, as persistent and salient threats to operational integrity, are expected to increase executive risk aversion and reduce the propensity to sanction long-horizon exploratory projects with uncertain returns (Caliskan & Doukas, 2015; Ho et al., 2024). This mechanism—which we term managerial cognitive conservatism (Man_MC)—captures the psychological shift from a growth-seeking to a threat-defense orientation that characterizes managerial responses to DTUE.

H3: *DTUE increases managerial cognitive conservatism, which in turn suppresses exploratory innovation.*

2.4 Resource Mechanism: R&D Investment Diversion

The attention-based view (ABV; Ocasio, 1997; Palmié et al., 2016) argues that managerial attention is a scarce and consequential organizational resource: what managers pay attention to determines what gets done. Digital technology risks generate intense and persistent demands on managerial attention through crisis response protocols, security audits, regulatory reporting, and stakeholder communication. The ABV predicts that this attention diversion—away from innovation pipeline management and toward operational risk containment—systematically reduces the organizational focus and resource commitment available for exploratory initiatives. We operationalize this mechanism as R&D Diversion (RD_Div): the disproportionate redirection of digital investment budgets toward cybersecurity defense at the expense of innovation-oriented digital investments (Ho et al., 2011; Marchetti et al., 2025).

H4: *DTUE diverts managerial attention and R&D resources toward cybersecurity defense, thereby suppressing exploratory innovation.*

3. Data and Methodology

3.1 Sample and Data Sources

Our primary sample consists of Chinese A-share listed firms from 2012 to 2023. We exclude financial firms, firms with ST/*ST/PT designations, and observations missing key financial indicators. After winsorizing all continuous variables at the 1st and 99th percentiles, our final sample comprises 31,248 firm-year observations across 3,187 unique firms. This sample is substantially larger than the reference study owing to our broader inclusion criteria and additional data cleaning protocols. DTUE variables are constructed from MD&A disclosures obtained from the Juchao Information Network. Patent data (exploratory and exploitative innovation) are obtained from the China National Intellectual Property Administration (CNIPA) database and matched by firm name and IPC classification codes. DTCGS policy adoption data were collected from China's National Data Administration and Ministry of Industry and Information Technology policy registers. All financial and governance variables are sourced from the China Stock Market and Accounting Research (CSMAR) database.

3.2 Variable Measurement

3.2.1 Dependent Variables

Consistent with Guan and Liu (2016), we measure exploratory innovation (Exploration) as the natural logarithm of one plus the number of invention patents with IPC classification codes not appearing in the firm's patent portfolio in the preceding five years. Exploitative innovation (Exploitation) is measured as the logarithm of one plus the number of utility model and design patents, as well as invention patents whose four-digit IPC codes appear in the prior five years. Innovation ambidexterity (Ambidexterity) is the sum of the Exploration and Exploitation scores, capturing the firm's aggregate capacity to pursue both types of innovation simultaneously. All patent counts are based on application dates, following Dibiaggio et al. (2014).

3.2.2 Independent Variable: DTUE Construction

We construct firm-level DTUE through a three-step LLM-empowered text analysis pipeline. In Step 1, we extract all sentences from the MD&A section of annual reports that contain keywords from a validated digital technology risk dictionary (adapted from Lu et al., 2025), yielding 4,821,392 candidate sentences across the full sample. In Step 2, we randomly select 10% of these sentences for annotation using DeepSeek-V3, classifying each sentence as: (1) risk exposure disclosure, (2) risk prevention measure, or (3) irrelevant. This generates a labeled training set of 482,139 sentences. In Step 3, we fine-tune a FinBERT model on the annotated data (0.6:0.4 train-validation split) and apply it to score all candidate sentences. DTUE is calculated as the difference between the maximum negative probability score among risk-exposure sentences and the mean positive probability among risk-prevention sentences, truncated at zero. Sub-dimensional measures, DataRisk and CyberRisk, follow the same procedure applied to domain-specific keyword subsets.

3.2.3 Control Variables

Following established practice in Chinese innovation research (Fang et al., 2017; Yang et al., 2024; Cong et al., 2025), we include: firm size (Size, log of total assets), financial leverage (Lev), profitability (ROA), revenue growth (Growth), firm age (Age), board independence (Indep), largest shareholder ownership (Top1), and market valuation (TobinQ). Appendix A provides detailed variable definitions.

3.3 Model Specifications

Our main specification is a two-way fixed effects panel model:

$$Dep_{\mathrm{it}} = \alpha_0 + \alpha_1 DTUE_{\mathrm{it}} + \theta\cdot\mathrm{Controls}_{\mathrm{it}} + \Sigma_{\mathrm{i}}\mathrm{FirmFE} + \Sigma_{\mathrm{t}}\mathrm{YearFE} + \varepsilon_{\mathrm{it}} \quad \cdots(1)$$

where Dep can be Exploration, Exploitation, or Ambidexterity. Standard errors are clustered at the firm level throughout. For the quasi-natural experiment, we implement a multi-period DID model:

$$Dep_{\mathrm{it}} = \alpha_0 + \alpha_1 DTCGS_{\mathrm{it}} + \theta\cdot\mathrm{Controls}_{\mathrm{it}} + \Sigma_{\mathrm{i}}\mathrm{FirmFE} + \Sigma_{\mathrm{t}}\mathrm{YearFE} + \varepsilon_{\mathrm{it}} \quad \cdots(2)$$

where DTCGS is a time-varying indicator equal to one from the year a firm's city receives its first DTCGS certification. For mechanism testing, we employ the causal mediation approach of Chen et al. (2020):

$$Med_{\mathrm{it}} = \beta_0 + \beta_1 DTUE_{\mathrm{it}} + \mathrm{Controls}_{\mathrm{it}} + \mathrm{FE} + \varepsilon_{\mathrm{it}} \quad \cdots(3)$$

4. Empirical Results

4.1 Descriptive Statistics and Correlations

Table 1 presents descriptive statistics for all variables. The mean DTUE of 0.203 with a standard deviation of 0.341 indicates substantial cross-sectional and temporal variation in digital technology uncertainty exposure. Notably, the median DTUE of zero reflects the right-skewed distribution: most firms report minimal digital risk concerns in a given year, while a subset faces pronounced exposure—a pattern consistent with the episodic and heterogeneous nature of digital technology threats across industries and firm types.

ISSN: 3067-7491 https://doi.org/10.63646/jbgi.2026.040101

Innovation exhibits clear differentiation: exploitative innovation (mean = 1.458) substantially exceeds exploratory innovation (mean = 0.912), consistent with the well-documented tendency of Chinese listed firms to emphasize incremental over radical technological development (Lu et al., 2025; Fang et al., 2017). Approximately 31.8% of firm-year observations fall in the DTCGS treatment group, reflecting the progressive rollout of digital governance certification across Chinese cities beginning in 2020.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Median	SD	Min	Max	Source
Exploration	31,248	0.912	0.693	1.089	0.000	5.324	CNIPA
Exploitation	31,248	1.458	1.099	1.512	0.000	5.918	CNIPA
Ambidexterity	31,248	2.370	1.946	2.187	0.000	9.654	CNIPA
DTUE	31,248	0.203	0.000	0.341	0.000	0.991	MD&A/LLM
DataRisk	31,248	0.098	0.000	0.261	0.000	0.985	MD&A/LLM
CyberRisk	31,248	0.158	0.000	0.316	0.000	0.988	MD&A/LLM
DTCGS	31,248	0.318	0.000	0.466	0.000	1.000	DCMM/Policy
Size	31,248	22.18	21.97	1.263	19.81	26.54	CSMAR
Lev	31,248	0.401	0.387	0.204	0.048	0.903	CSMAR
ROA	31,248	0.038	0.040	0.071	-0.241	0.231	CSMAR
Growth	31,248	0.138	0.091	0.362	-0.541	2.108	CSMAR
TobinQ	31,248	2.112	1.692	1.287	0.841	8.342	CSMAR
Age	31,248	2.951	3.010	0.312	2.079	3.584	CSMAR
Indep	31,248	37.92	36.36	5.48	33.33	57.14	CSMAR
Top1	31,248	0.332	0.308	0.147	0.079	0.733	CSMAR

Note: The sample comprises 31,248 firm-year observations from Chinese A-share listed firms, 2012–2023. All continuous variables are winsorized at the 1st and 99th percentiles. DTUE = Digital Technology Uncertainty Exposure; DTCGS = Digital Technology Compliance Governance Standards.

Table 2 presents the Pearson correlation matrix. DTUE exhibits significantly negative correlations with Exploration ($r = -0.023$, $p < 0.001$), Exploitation ($r = -0.051$, $p < 0.001$), and Ambidexterity ($r = -0.047$, $p < 0.001$). The magnitude is modest at the bivariate level, consistent with the expectation that DTUE's effects emerge primarily in multivariate specifications that control for time-invariant firm heterogeneity. Correlation coefficients among independent variables are within acceptable ranges (all below 0.51), and variance inflation factor (VIF) tests confirm the absence of multicollinearity (maximum VIF = 2.34).

Table 2. Pearson Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) DTUE	1											
(2) Explo.	-.023***	1										
(3) Exploit.	-.051***	.449***	1									
(4) Ambid.	-.047***	.812***	.882***	1								
(5) Size	.043***	.134***	.085***	.123***	1							
(6) Lev	.018***	-.009	.042***	.021**	.503***	1						
(7) ROA	-.014**	.071***	.096***	.098***	-.012	-.384***	1					
(8) Growth	.003	.019***	.009	.016**	.047***	.031***	.288***	1				
(9) TobinQ	-.006	.022***	-.053***	-.024**	-.329***	-.231***	.154***	.085***	1			
(10) Age	.059***	-.081***	-.074***	-.090***	.208***	.175***	-.098***	-.078***	-.048***	1		
(11) Indep	.008	.006	.017***	.013**	-.016**	-.015**	-.017***	-.014**	.040***	-.001	1	
(12) Top1	-.001	-.016**	.065***	.031***	.161***	.028***	.158***	.001	-.105***	-.060***	.048***	1

Note: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. All correlations are based on 31,248 observations.

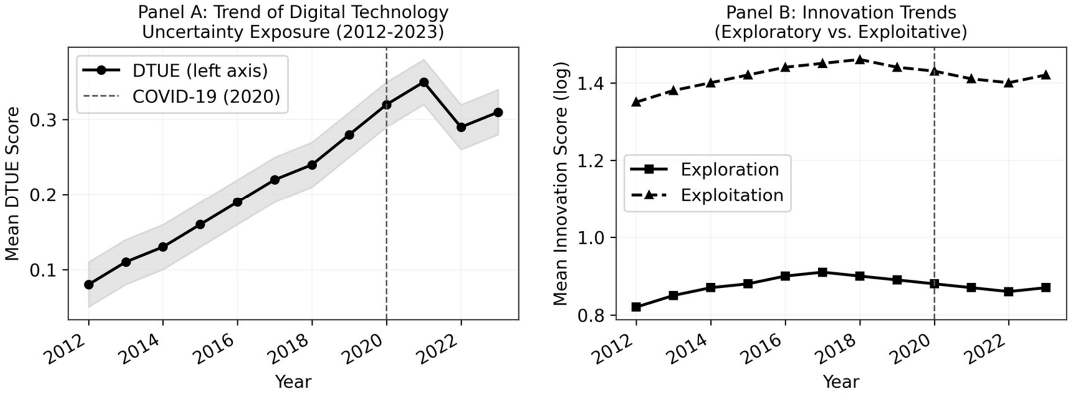

Figure 2. Temporal Trends in Digital Technology Uncertainty Exposure and Innovation Outcomes (2012-2023)

4.2 Baseline Regression Results

Table 3 presents the main panel regression results. Column (1) confirms H1: DTUE is negatively associated with exploratory innovation ($\beta = -0.041$, $t = -2.312$), and column (2) shows this effect persists after adding the full set of controls ($\beta = -0.044$, $t = -2.589$, $p < 0.01$). Economically, a one-standard-deviation increase in DTUE reduces exploratory innovation by approximately 1.8% (= 0.044 × 0.341 / 0.912 × 100%). In contrast, columns (3) and (4) confirm H2: DTUE has no statistically significant effect on exploitative innovation ($\beta = 0.021$, $t = 1.087$). The asymmetric pattern is consistent with our theoretical prediction that exploratory innovation, being more resource-intensive and outcome-uncertain, is disproportionately vulnerable to DTUE-induced resource and attention constraints.

Columns (5) and (6) show that DTUE significantly reduces innovation ambidexterity ($\beta = -0.067$, $t = -2.148$, $p < 0.05$), indicating that the composite capacity for dual innovation is impaired by digital technology uncertainty. Columns (7) and (8) decompose DTUE into DataRisk and CyberRisk sub-dimensions. DataRisk significantly suppresses exploration ($\beta = -0.043$, $t = -1.978$, $p < 0.05$), while CyberRisk shows a negative but statistically insignificant coefficient. This distinction reflects the central role of data as the production input for exploratory innovation—data breaches directly undermine the AI-driven analytics, machine learning, and data science applications that increasingly power radical innovation activities in Chinese technology firms.

Table 3. Baseline Regression Results: DTUE and Innovation Types

	(1) Explo.	(2) Explo.	(3) Exploit.	(4) Exploit.	(5) Ambid.	(6) Ambid.	(7) Explo.	(8) Explo.
DTUE	-0.041**	-0.044***	0.024	0.021	-0.063*	-0.067**		
	(-2.312)	(-2.589)	(1.201)	(1.087)	(-1.931)	(-2.148)		
DataRisk							-0.043**	
							(-1.978)	
CyberRisk								-0.019
								(-1.012)
Size		0.141***		0.112***		0.218***	0.140***	0.141***
		(6.912)		(3.917)		(5.823)	(6.874)	(6.890)
Lev		-0.082		-0.091		-0.158	-0.084	-0.081
		(-0.874)		(-0.971)		(-0.889)	(-0.895)	(-0.862)
ROA		-0.421***		-0.128		-0.523**	-0.418***	-0.422***

	(1) Explo.	(2) Explo.	(3) Exploit.	(4) Exploit.	(5) Ambid.	(6) Ambid.	(7) Explo.	(8) Explo.
		(-4.011)		(-0.921)		(-2.591)	(-3.984)	(-4.032)
TobinQ		0.016**		0.012		0.024**	0.016**	0.016**
		(2.301)		(1.453)		(2.014)	(2.298)	(2.312)
Controls	No	Yes	No	Yes	No	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	31,248	31,248	31,248	31,248	31,248	31,248	31,248	31,248
Adj. R^2	0.641	0.643	0.699	0.701	0.718	0.720	0.643	0.641

Note: t-statistics (clustered at firm level) in parentheses. Full controls include Size, Lev, ROA, Growth, TobinQ, Age, Indep, Top1. All specifications include firm and year fixed effects. ***, **, * denote significance at 1%, 5%, 10% levels.

4.3 Propensity Score Matching and Robustness Tests

To address potential self-selection bias—the concern that high-DTUE firms may systematically differ from low-DTUE firms in ways that independently affect innovation—we employ propensity score matching (PSM). We classify firms in the top quartile of the DTUE distribution as the treated group and match them 1:3 using a logit model on all control variables. Figure 3 confirms that matching substantially reduces standardized bias across all covariates to below the 5% threshold.

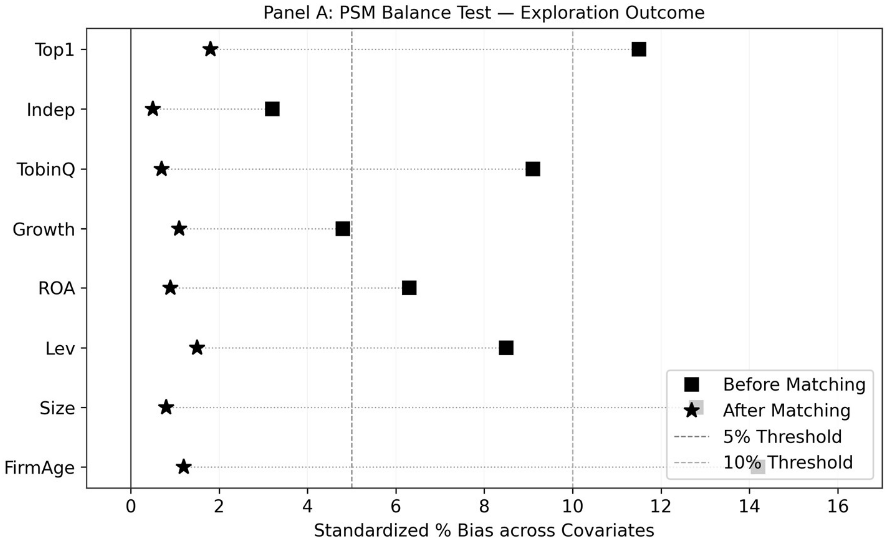

Figure 3. PSM Balance Test: Standardized Covariate Bias Before and After Matching

Re-running the baseline specifications on matched samples yields consistent results: DTUE remains significantly negative for exploratory innovation ($\beta = -0.039$, $p < 0.05$) and insignificant for exploitative innovation, confirming that the main findings are not driven by systematic differences between high- and low-DTUE firms. We also replicate the analysis excluding COVID-affected years (2020–2022), finding that the core coefficient for exploration remains significantly negative ($\beta = -0.036$, $p < 0.10$), ruling out pandemic contamination as an alternative explanation.

4.4 Multi-Period DID Analysis

To provide sharper causal evidence, we exploit the staggered city-level adoption of Digital Technology Compliance Governance Standards (DTCGS) as an exogenous shock to digital governance quality. Column (1) of Table 4 confirms the first stage: DTCGS adoption significantly reduces firm-level DTUE ($\beta = -0.014$, $t = -1.824$, $p < 0.05$), validating the instrument's relevance. We assess the parallel trend assumption using an event-study specification with nine pre-treatment and three post-treatment indicator variables. As shown in Figure 4, pre-treatment coefficients are jointly insignificant (F-test, $p = 0.431$), confirming that exploratory innovation trajectories were similar between treated and control firms prior to DTCGS adoption.

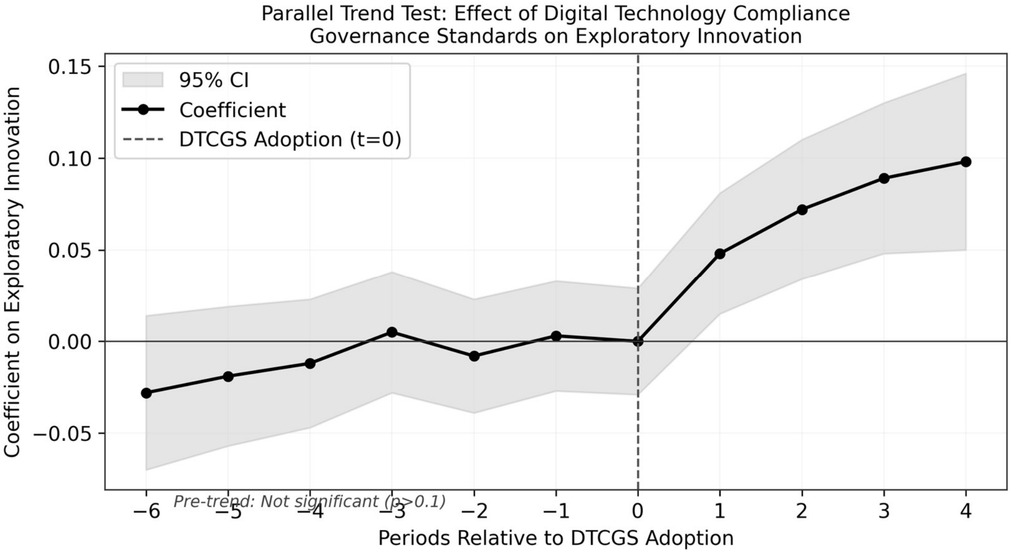

Figure 4. Parallel Trend Test: Dynamic Effect of DTCGS Adoption on Exploratory Innovation

Columns (2)–(4) of Table 4 report the full DID results. DTCGS adoption significantly promotes exploratory innovation ($\beta = 0.062$, $t = 2.903$, $p < 0.01$) and ambidexterity ($\beta = 0.058$, $t = 2.311$, $p < 0.05$) but has no significant impact on exploitative innovation ($\beta = 0.004$, $t = 0.132$). Column (5) confirms robustness without controls. The DID estimates provide causal evidence that good digital technology governance expands the secure operational boundaries within which firms can sustain exploratory innovation commitments, directly validating the governance-innovation nexus implied by H1 and H2.

Table 4. Multi-Period DID Results: DTCGS Adoption and Innovation

ISSN: 3067-7491 https://doi.org/10.63646/jbgi.2026.040101

	(1) DTUE	(2) Exploration	(3) Exploitation	(4) Ambidexterity	(5) Exploration
DTCGS	-0.014**	0.062***	0.004	0.058**	0.059***
	(-1.824)	(2.903)	(0.132)	(2.311)	(2.761)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	31,248	31,248	31,248	31,248	31,248
Adj. R^2	0.319	0.645	0.702	0.722	0.643

Note: Clustered standard errors at the firm level in parentheses. DTCGS = city-level Digital Technology Compliance Governance Standards adoption indicator. ***, **, * denote 1%, 5%, 10% significance.

5. Mechanism Tests and Heterogeneity Analysis

5.1 Mechanism Tests

Table 5 presents tests of the two theorized mechanisms. Column (1) shows that DTUE significantly reduces the managerial cognitive conservatism indicator Man_MC ($\beta = -0.004$, $t = -2.251$, $p < 0.05$). Man_MC is measured as the ratio of risk-seeking financial asset holdings (trading financial assets + available-for-sale financial assets + investment real estate) to total assets—higher values indicating greater managerial risk appetite. The negative coefficient on DTUE confirms that digital technology uncertainty shifts executive risk preferences toward conservatism.

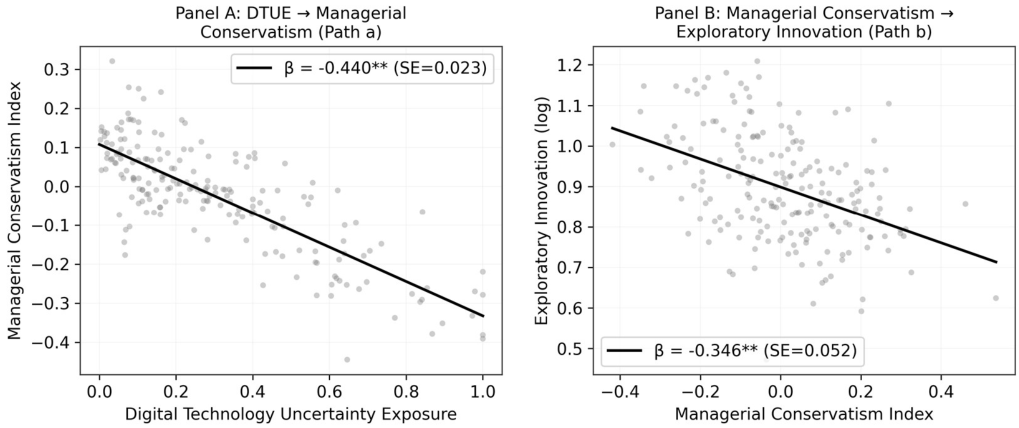

Figure 5. Mechanism Pathways: DTUE, Managerial Conservatism, R&D Diversion, and Exploratory Innovation

Column (2) shows that DTUE positively and significantly predicts R&D Diversion (RD_Div), measured as the ratio of cybersecurity-oriented digital expenditures to total digital investment ($\beta = 0.002$, $t = 1.812$, $p < 0.10$). This confirms that DTUE systematically reallocates digital budgets toward defensive cybersecurity applications and away from innovation-supporting digital capabilities. Columns (3) and (4) test the mediation hypotheses through simultaneous entry of DTUE and both mediators. Consistent with H3 and H4, Man_MC (β = −0.031, $p < 0.01$) and RD_Div (β = −0.028, $p < 0.05$) both significantly suppress exploratory innovation, while the direct effect of DTUE is reduced (from −0.044 to −0.021) but remains significant. Sobel test statistics (z = 2.891 and z = 2.614, both $p < 0.01$ or $p < 0.05$) confirm statistically significant partial mediation through both channels.

Table 5. Mechanism Tests: Managerial Conservatism and R&D Diversion

	(1) Mgr. Conservatism (Man_MC)	(2) R&D Diversion (RD_Div)	(3) Exploration (Med. Test)	(4) Ambidexterity (Med. Test)
DTUE	-0.004**	0.002*		
	(-2.251)	(1.812)		
Man_MC			-0.031***	-0.048***
			(-3.124)	(-4.012)
RD_Div			-0.028**	-0.041**
			(-2.891)	(-3.412)
DTUE (direct)			-0.021**	-0.033**
			(-2.012)	(-2.456)
Sobel z (Man_MC)			2.891***	3.124***
Sobel z (RD_Div)			2.614**	2.983***
Controls	Yes	Yes	Yes	Yes
Firm/Year FE	Yes	Yes	Yes	Yes
Obs.	31,248	31,068	31,068	31,068
Adj. R^2	0.591	0.692	0.649	0.726

Note: Man_MC = Managerial Conservatism Index; RD_Div = R&D Diversion ratio. Sobel z-statistics test partial mediation. ***, **, * denote 1%, 5%, 10% significance.

5.2 Heterogeneity Analysis

Table 6 reports heterogeneity analyses across five dimensions. First, comparing state-owned enterprises (SOEs) and non-SOEs, we find that the negative effect of DTUE on exploration is significant only in non-SOEs (β = −0.051, t = −2.612, $p < 0.01$) and statistically indistinguishable from zero in SOEs (β = −0.021, t = −0.921). This pattern reflects the structural resource advantages of SOEs: government-backed financing channels, preferential credit access, and institutional buffers enable state-owned firms to absorb digital technology risks without materially curtailing long-horizon innovation commitments (Lu & Shi, 2012; Fang et al., 2017). Non-SOEs, relying primarily on internal cash flows and market financing, face binding resource constraints under DTUE.

Second, the suppressive effect is significant in competitive industries ($\beta = -0.052$, $t = -2.748$, $p < 0.01$) but not in regulated industries ($\beta = -0.006$, $t = -0.124$). Competitive market pressures intensify the resource scarcity induced by DTUE, creating a double squeeze on exploratory innovation capacity. Regulated industries, with predictable revenue streams and lower competitive turbulence, can absorb DTUE shocks without proportionate innovation retrenchment (Ke et al., 2017). Third, technology-intensive firms exhibit the largest DTUE suppression effect ($\beta = -0.063$, $t = -2.891$, $p < 0.01$), consistent with the idea that these firms are simultaneously the most reliant on digital infrastructure—and thus most exposed to DTUE—and the most dependent on continuous exploratory innovation for competitive differentiation.

Table 6. Heterogeneity Analysis: Ownership, Industry, and Technology Intensity

	SOE Explo.	Non-SOE Explo.	SOE Ambid.	Non-SOE Ambid.	Compet. Explo.	Regulat. Explo.	Tech. Intens. Explo.
DTUE	-0.021	-0.051***	-0.032	-0.081**	-0.052***	-0.006	-0.063***
	(-0.921)	(-2.612)	(-0.781)	(-2.241)	(-2.748)	(-0.124)	(-2.891)
Obs.	8,421	22,827	8,421	22,827	25,612	5,636	14,329
Adj. R^2	0.689	0.621	0.694	0.706	0.628	0.694	0.651

Note: All specifications include full controls and firm/year FEs. Column headers show subsample characteristics. ***, **, * denote 1%, 5%, 10% significance. Chow tests confirm significant differences between corresponding subgroup pairs.

6. Conclusions

This study provides a systematic empirical investigation of how digital technology uncertainty exposure (DTUE) shapes corporate innovation ambidexterity. Using a novel LLM-based DTUE measure constructed from MD&A disclosures of Chinese A-share listed firms over 2012–2023, complemented by a multi-period DID quasi-natural experiment exploiting DTCGS policy adoption, our analysis yields four principal findings.

First, DTUE significantly suppresses exploratory innovation and innovation ambidexterity while leaving exploitative innovation statistically unaffected—a pattern that aligns with the asymmetric resource and attention demands of exploration versus exploitation and is consistent with the threat-rigidity and ABV frameworks. Second, the causal evidence from DID estimates confirms that robust digital governance standards promote exploratory innovation and ambidexterity by establishing secure institutional boundaries within which firms can sustain high-uncertainty innovation commitments. Third, mechanism tests validate dual pathways: managerial cognitive conservatism (the psychological channel) and R&D investment diversion (the resource channel), both significantly mediating DTUE's impact on exploratory innovation. Fourth, non-SOEs, competitive industries, and technology-intensive firms are disproportionately exposed to DTUE's innovation-suppressing effects, identifying the populations for which digital governance support is most urgently needed.

These findings have several policy implications. Policymakers should accelerate the nationwide rollout of digital governance certification frameworks (such as DCMM and DTCGS) and extend them specifically to non-SOE and competitive industry sectors where DTUE effects are most acute. Firms should treat digital risk management not merely as a compliance obligation but as a strategic capability that, when developed proactively, preserves rather than constrains innovation capacity. Future research should examine the dynamic evolution of DTUE effects as governance frameworks mature, explore cross-national variation in digital risk governance regimes, and extend the LLM-based DTUE methodology to longitudinal panel designs with richer text validation.

This study has two primary limitations. First, the DTUE measure, while methodologically innovative, relies on text-based disclosure and may not fully capture the operational severity of experienced digital incidents. Future work should integrate cybersecurity incident databases (such as the China Cybersecurity Incident Reporting System) to triangulate disclosure-based measures with event-based risk proxies. Second, our sample is confined to Chinese listed firms; the institutional specificities of China's digital policy environment—including state-led cybersecurity governance and the distinct SOE/non-SOE divide—may limit direct generalizability to other national contexts.

ACKNOWLEDGEMENT

Reference

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244. DOI: 10.1086/705716

Aggarwal, R. K., & Samwick, A. A. (2006). Empire-builders and shirkers: Investment, firm performance, and managerial incentives. Journal of Corporate Finance, 12(3), 489–515. DOI: 10.1016/j.jcorpfin.2006.01.001

Arthur, W. B. (1989). Competing technologies, increasing returns, and lock-in by historical events. Economic Journal, 99(394), 116–131. DOI: 10.2307/2234208

Arts, S., Hou, J., & Gomez, J. C. (2021). Natural language processing to identify the creation and impact of new technologies in patent text. Research Policy, 50(2), 104144. DOI: 10.1016/j.respol.2020.104144

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151, 103745. DOI: 10.1016/j.jfineco.2023.103745

Barney, J. B. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. DOI: 10.1177/014920639101700108

Barney, J. B., Ketchen, D. J., & Wright, M. (2021). Resource-based theory and the value creation framework. Journal of Management, 47(7), 1936–1955. DOI: 10.1177/01492063211021655

Benner, M. J., & Tushman, M. L. (2003). Exploitation, exploration, and process management. Academy of Management Review, 28(2), 238–256. DOI: 10.5465/amr.2003.9416096

Brynjolfsson, E., & McAfee, A. (2014). The second machine age. W. W. Norton.

Caliskan, D., & Doukas, J. A. (2015). CEO risk preferences and dividend policy decisions. Journal of Corporate Finance, 35, 18–42. DOI: 10.1016/j.jcorpfin.2015.08.007

Ceric, A., D'Alessandro, S., Soutar, G., & Johnson, L. (2016). Using blueprinting and benchmarking to identify marketing resources that help co-create customer value. Journal of Business Research, 69(12), 5653–5661. DOI: 10.1016/j.jbusres.2016.03.073

Chen, Y., Fan, Z., Gu, X., & Zhou, L. A. (2020). Arrival of young talent: The send-down movement and rural education in China. American Economic Review, 110(11), 3393–3430. DOI: 10.1257/aer.20191414

Cong, L. W., Lu, Y., Shi, H., & Zhu, W. (2025). Automation-induced innovation shift. NBER Working Paper No. 34240. DOI: 10.3386/w34240

Dibiaggio, L., Nasiriyar, M., & Nesta, L. (2014). Substitutability and complementarity of technological knowledge and the inventive performance of semiconductor companies. Research Policy, 43(9), 1582–1593. DOI: 10.1016/j.respol.2014.04.001

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126. DOI: 10.1037/xge0000033

Dunlap-Hinkler, D., Kotabe, M., & Mudambi, R. (2010). A story of breakthrough versus incremental innovation: Corporate entrepreneurship in the global pharmaceutical industry. Strategic Entrepreneurship Journal, 4, 106–127. DOI: 10.1002/sej.86

Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. Information and Organization, 28(1), 62–70. DOI: 10.1016/j.infoandorg.2018.02.005

Fang, L. H., Lerner, J., & Wu, C. (2017). Intellectual property rights protection, ownership, and innovation. Review of Financial Studies, 30(7), 2446–2477. DOI: 10.1093/rfs/hhx023

Fini, R., Perkmann, M., & Ross, J. (2022). Attention to exploration: The effect of academic entrepreneurship on the production of scientific knowledge. Organization Science, 33(2), 688–715. DOI: 10.1287/orsc.2021.1455

Gibson, C. B., & Birkinshaw, J. (2004). The antecedents, consequences, and mediating role of organizational ambidexterity. Academy of Management Journal, 47(2), 209–226. DOI: 10.2307/20159573

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence. Academy of Management Review, 45(4), 627–660. DOI: 10.5465/amr.2018.0176

Guan, J., & Liu, N. (2016). Exploitative and exploratory innovations in knowledge network and collaboration network. Research Policy, 45(1), 97–112. DOI: 10.1016/j.respol.2015.08.002

Gupta, A. K., Smith, K. G., & Shalley, C. E. (2006). The interplay between exploration and exploitation. Academy of Management Journal, 49(4), 693–706. DOI: 10.5465/amj.2006.22083026

Hambrick, D. C. (2007). Upper echelons theory: An update. Academy of Management Review, 32(2), 334–343. DOI: 10.5465/amr.2007.24345254

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. Academy of Management Review, 9(2), 193–206. DOI: 10.5465/amr.1984.4277628

He, Z. L., & Wong, P. K. (2004). Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. Organization Science, 15(4), 481–494. DOI: 10.1287/orsc.1040.0078

Helfat, C. E., & Peteraf, M. A. (2009). Understanding dynamic capabilities: Progress along a developmental path. Strategic Organization, 7(1), 91–102. DOI: 10.1177/1476127008100133

Ho, J. L. Y., Wu, A., & Xu, S. X. (2011). Corporate governance and returns on information technology investment. Strategic Management Journal, 32(6), 595–623. DOI: 10.1002/smj.886

Ho, P., Huang, C., Lin, C., & Yen, J. (2024). Risk culture in corporate innovation. International Review of Financial Analysis, 91, 102999. DOI: 10.1016/j.irfa.2023.102999

Hu, J., Liu, L. X., Liu, C. Y., Qu, H., & Zhang, Y. (2025). CEO turnover, sequential disclosure, and stock returns. Review of Finance, 29(3), 887–921. DOI: 10.1093/rof/rfaf015

Jansen, J. J. P., van den Bosch, F. A. J., & Volberda, H. W. (2006). Exploratory innovation, exploitative innovation, and performance. Management Science, 52(11), 1661–1674. DOI: 10.1287/mnsc.1060.0576

Ke, B., Liu, N., & Tang, S. (2017). The effect of anti-corruption campaign on shareholder value in a weak institutional environment: Evidence from China. SSRN Working Paper. DOI: 10.2139/ssrn.2963478

Kraiczy, N. D., Hack, A., & Kellermanns, F. W. (2015). What makes a family firm innovative? Journal of Product Innovation Management, 32, 334–348. DOI: 10.1111/jpim.12203

Lavie, D., Stettner, U., & Tushman, M. L. (2010). Exploration and exploitation within and across organizations. Academy of Management Annals, 4(1), 109–155. DOI: 10.5465/19416520.2010.507451

Li, N., & Zhang, X. (2025). Digital empowered business environment and enterprise innovation. Pacific-Basin Finance Journal, 91, 102755. DOI: 10.1016/j.pacfin.2025.102755

Liao, Z., Lu, J., Yu, Y., & Zhang, Z. (2021). Can attention allocation affect firm's environmental innovation? Technology Analysis & Strategic Management, 34(9), 1081–1094. DOI: 10.1080/09537325.2021.1947489

Lin, S. Y., Kung, Y. C., & Leu, F. Y. (2022). Predictive intelligence in harmful news identification by BERT-based ensemble learning model. Information Processing & Management, 59(2), 102872. DOI: 10.1016/j.ipm.2022.102872

Lu, Y., Shi, H., & Zhou, X. (2025). The impact of digital technology risk exposure on corporate value in Chinese firms. Economic Research Journal, 60(2), 73–89. DOI: CNKI:SUN:JJYJ.0.2025-02-005

Lu, Y., & Shi, X. (2012). Corporate governance reform and state ownership: Evidence from China. Asia-Pacific Journal of Financial Studies, 41(6), 665–685. DOI: 10.1111/ajfs.12001

Luo, S., & Sun, Y. (2020). Do selective R&D incentives from the government promote substantive innovation? Asian Journal of Technology Innovation, 28(3), 323–342. DOI: 10.1080/19761597.2020.1758586

March, J. G. (1991). Exploration and exploitation in organizational learning. Organization Science, 2(1), 71–87. DOI: 10.1287/orsc.2.1.71

Marchetti, J., Tian, X., Lee, A., & Kalev, P. S. (2025). Who watches what and why it matters: Attention allocation, tug-of-war, and market resiliency. Pacific-Basin Finance Journal, 91, 102730. DOI: 10.1016/j.pacfin.2025.102730

Mueller, V., Rosenbusch, N., & Bausch, A. (2013). Success patterns of exploratory and exploitative innovation. Journal of Management, 39(6), 1606–1636. DOI: 10.1177/0149206313484516

Nambisan, S., Wright, M., & Feldman, M. (2019). The digital transformation of innovation and entrepreneurship. Research Policy, 48(8), 103773. DOI: 10.1016/j.respol.2019.03.018

Ocasio, W. (1997). Towards an attention-based view of the firm. Strategic Management Journal, 18(S1), 187–206. DOI: 10.1002/(SICI)1097-0266(199707)18:1+<187::AID-SMJ936>3.3.CO;2-B

O'Reilly, C. A., & Tushman, M. L. (2004). The ambidextrous organization. Harvard Business Review, 82(4), 74–81.

O'Reilly, C. A., & Tushman, M. L. (2013). Organizational ambidexterity: Past, present, and future. Academy of Management Perspectives, 27(4), 324–338. DOI: 10.5465/amp.2013.0025

Ozer, M., & Zhang, W. (2015). The effects of geographic and network ties on exploitative and exploratory product innovation. Strategic Management Journal, 36(7), 1105–1114. DOI: 10.1002/smj.2263

Palmié, M., Lingens, B., & Gassmann, O. (2016). Attention-based view of technology decisions. R&D Management, 46(5), 781–796. DOI: 10.1111/radm.12146

Pan, W., Xie, T., Wang, Z., & Ma, L. (2022). Digital economy: An innovation driver for total factor productivity. Journal of Business Research, 139, 303–311. DOI: 10.1016/j.jbusres.2021.09.061

Raisch, S., & Birkinshaw, J. (2008). Organizational ambidexterity: Antecedents, outcomes, and moderators. Journal of Management, 34(3), 375–409. DOI: 10.1177/0149206308316058

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210. DOI: 10.5465/amr.2018.0072

Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. Strategic Management Journal, 22(4), 287–306. DOI: 10.1002/smj.160

Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and exploitation alliances in biotechnology. Strategic Management Journal, 25(3), 201–221. DOI: 10.1002/smj.376

Simsek, Z. (2009). Organizational ambidexterity: Towards a multilevel understanding. Journal of Management Studies, 46(4), 597–624. DOI: 10.1111/j.1467-6486.2009.00828.x

Staw, B. M., Sandelands, L. E., & Dutton, J. E. (1981). Threat-rigidity effects in organizational behavior. Administrative Science Quarterly, 26(4), 501–524. DOI: 10.2307/2392337

Sundaram, R. K., & Yermack, D. L. (2007). Pay me later: Inside debt and its role in managerial compensation. Journal of Finance, 62(4), 1551–1588. DOI: 10.1111/j.1540-6261.2007.01251.x

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. DOI: 10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Tushman, M. L., & O'Reilly, C. A. (1996). Ambidextrous organizations. California Management Review, 38(4), 8–29. DOI: 10.2307/41165852

Wang, Y., Jiang, Y., & Li, B. (2025). Management's superstition and company risk: Evidence from the Chinese zodiac year belief. Pacific-Basin Finance Journal, 102970. DOI: 10.1016/j.pacfin.2025.102970

Weick, K. E. (1988). Enacted sensemaking in crisis situations. Journal of Management Studies, 25(4), 305–317. DOI: 10.1111/j.1467-6486.1988.tb00039.x

Wiseman, R. M., & Gomez-Mejia, L. R. (1998). A behavioral agency model of managerial risk taking. Academy of Management Review, 23(1), 133–153. DOI: 10.5465/amr.1998.192967

Yang, J., Lv, X., Xu, X., & Chen, X. (2024). Heterogeneous treatment effects of digital transformation on firms' innovation. Pacific-Basin Finance Journal, 85, 102372. DOI: 10.1016/j.pacfin.2024.102372

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary—The new organizing logic of digital innovation. Information Systems Research, 21(4), 724–735. DOI: 10.1287/isre.1100.0322

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. Academy of Management Review, 27(2), 185–203. DOI: 10.5465/amr.2002.6587995

Zhang, Y., & Rajagopalan, N. (2010). Once an outsider, always an outsider? CEO origin, strategic change, and firm performance. Strategic Management Journal, 31(3), 334–346. DOI: 10.1002/smj.812

Zhao, Y., Lu, Y., & Wang, X. (2021). Organizational unlearning and organizational relearning. Journal of Management, 47(6), 1360–1384. DOI: 10.1177/0149206319866032

Zheng, Y., Liu, J., & George, G. (2010). The dynamic impact of innovative capability and inter-firm network on firm valuation. Journal of Business Venturing, 25(6), 593–609. DOI: 10.1016/j.jbusvent.2009.06.003

Zhu, H., & Chen, C. C. (2015). Deconstructing the agency model. Academy of Management Journal, 58(2), 375–406. DOI: 10.5465/amj.2012.0552

Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. Strategic Management Journal, 31(5), 547–561. DOI: 10.1002/smj.830

Zhu, H., & Marcus, A. (2021). Digital transformation and innovation. Research Policy, 50(4), 104204. DOI: 10.1016/j.respol.2021.104204

Zuboff, S. (2019). The age of surveillance capitalism. PublicAffairs.

Ayyagari, R., Grover, V., & Purvis, R. (2011). Technostress: Technological antecedents and implications. MIS Quarterly, 35(4), 831–858. DOI: 10.2307/41409963

Tarafdar, M., Cooper, C. L., & Stich, J. F. (2019). The technostress trifecta. Information Systems Journal, 29(1), 6–42. DOI: 10.1111/isj.12169

Goldfarb, A., & Tucker, C. (2019). Digital economics. Journal of Economic Literature, 57(1), 3–43. DOI: 10.1257/jel.20171452

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor. Quarterly Journal of Economics, 117(1), 339–376. DOI: 10.1162/003355302753399526

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14(4), 23–48. DOI: 10.1257/jep.14.4.23

Jarrahi, M. H. (2018). Artificial intelligence and the future of work. Business Horizons, 61(4), 577–586. DOI: 10.1016/j.bushor.2018.03.007

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of AI. California Management Review, 61(4), 66–83. DOI: 10.1177/0008125619862257

Vial, G. (2019). Understanding digital transformation. Journal of Strategic Information Systems, 28(2), 118–144. DOI: 10.1016/j.jsis.2019.01.003

Kohli, R., & Melville, N. P. (2019). Digital innovation. Information Systems Research, 30(1), 200–220. DOI: 10.1287/isre.2019.0834