

RESEARCH ARTICLE

Demographic transition, digital transformation,
and intergenerational knowledge transfer in
firms: A study on ambidextrous innovation
performance based on dynamic capabilities

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Abstract

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Against the backdrop of global population aging and the rapid expansion of the digital economy, firms face the dual challenge of changing intergenerational workforce structures and digital transformation. This study is situated within the dynamic capabilities stream and asks how macro-level demographic and digital transitions translate into firm-level ambidextrous innovation through intergenerational knowledge routines. Grounded in dynamic capabilities theory, the study constructs a mechanism-based framework linking firm-level demographic transition, digital transformation, intergenerational knowledge transfer, dynamic capabilities, and ambidextrous innovation performance. Using 12,468 firm-level observations from the World Bank Enterprise Survey 2019–2023 across 32 countries, the analysis combines hierarchical regression, bootstrapped mediation and moderation tests, country and industry fixed effects, cluster-robust standard errors, alternative measurement checks, instrumental-variable sensitivity tests, developed- and emerging-economy subsample tests, and lag-effect tests. The results show that: (i) firm-level demographic transition has a significant inverted U-shaped effect on ambidextrous innovation performance, while digital transformation has a significant positive effect; (ii) intergenerational knowledge transfer partially mediates these relationships; (iii) dynamic capabilities positively moderate the inverted U-shaped relationship between demographic transition and intergenerational knowledge transfer, as well as the positive relationship between digital transformation and intergenerational knowledge transfer; and (iv) the indirect effects of demographic transition and digital transformation on ambidextrous innovation via intergenerational knowledge transfer are stronger for firms with high dynamic capabilities. The study contributes by identifying intergenerational knowledge transfer as a behavioral micro-foundation through which firms translate demographic and digital antecedents into innovation outcomes. The findings are interpreted as robust associations supported by additional identification checks, rather than as definitive causal proof.

Keywords: Demographic transition; Digital transformation; Intergenerational knowledge transfer; Ambidextrous innovation; Dynamic capabilities; Firm innovation performance

1. Introduction

According to the United Nations World Population Prospects (UNWPP, 2024), by 2050, people aged 65 and above are expected to account for about 16% of the global population, making workforce aging an increasingly irreversible trend. At the firm level, this demographic transition (DT) is reflected in changes in the intergenerational composition of employees: the retirement of older workers may lead to the loss of accumulated tacit knowledge, while the growing presence of younger cohorts strengthens digital skills and openness to new technologies but may also widen intergenerational communication gaps (Backes-Gellner & Veen, 2012; Mothe & Nguyen-Thi, 2021; Y. Wang & Shi, 2024). At the same time, digital transformation (DigiT) is reshaping how firms create, codify, store, and share knowledge. Technologies such as big data analytics, artificial intelligence, cloud collaboration platforms, and digital business systems increasingly affect firms' learning routines and innovation processes (Ellström *et al.*, 2021; Konopik *et al.*, 2022; Magistretti *et al.*, 2021; Nambisan *et al.*, 2019). Under these dual pressures, understanding how firms can respond to DT, leverage DigiT, and promote intergenerational knowledge transfer (IKT) has become an important managerial and academic issue.

Ambidextrous innovation, namely the joint pursuit of exploitative innovation (incremental improvements to existing products/processes) and exploratory innovation (the development of new products/markets), is a central outcome in strategic management research (He & Wong, 2004). Existing evidence is informative, but the relevant streams have not fully explained a common mechanism. Studies on workforce age structure demonstrate the consequences for productivity and innovation; studies on DigiT examine technology-enabled innovation; and dynamic capabilities (DC) research explains resource reconfiguration routines. However, these streams often stop at separate antecedent-outcome links. Three mechanism-level issues remain unresolved. First, workforce age structure is often modeled linearly, while theory implies a nonlinear process: moderate age diversity increases knowledge complementarity, whereas excessive aging or strong age polarization raises coordination frictions and may suppress innovation returns. Second, DigiT research frequently estimates direct effects of technology adoption on innovation, but the generational behavior mechanism through which digital tools are translated into ambidextrous outcomes is under-specified. Third, DC studies identify sensing, seizing, and transforming routines, yet few multi-country, firm-level studies test whether these routines jointly condition demographic and digital antecedents within a single integrated framework. Therefore, the gap addressed here is a mechanism-focused

integration gap within the DC and knowledge-based streams. The argument is not that prior integrative work is absent; rather, prior work has rarely cross-analyzed demographic and digital antecedents, generational knowledge behavior, firm-level DC, and national contexts in one empirical model.

To address these issues, this paper asks three research questions:

- (i) How do firm-level DT and DigiT affect ambidextrous innovation performance?
- (ii) Does IKT mediate these relationships?
- (iii) How do DC condition these mechanisms?

Because firms are embedded in different national institutions, labor markets, and digital infrastructures, the analysis treats the firm as the unit of analysis while modeling country characteristics as contextual heterogeneity. Using World Bank Enterprise Survey (WBES) firm-level data from 32 countries, this study contributes in three ways. First, it provides a large-sample cross-country test of the inverted U-shaped relationship between DT and ambidextrous innovation. Second, it identifies IKT as the mediating mechanism linking DT and DigiT to innovation performance, thereby clarifying the generational behavior mechanism behind the results. Third, it models DC as a boundary condition and compares patterns of effects across developed and emerging economies. Accordingly, this study refines and contextualizes existing theory rather than claiming to completely settle prior controversies.

Recent literature in strategic management, innovation management, and knowledge-based theory provides important building blocks. On the demographic side, knowledge transfer between younger and older employees depends on temporal comparison, reciprocal learning motives, generativity, development striving, and trust in age-diverse dyads (Burmeister *et al.*, 2020; Fasbender *et al.*, 2021; Fasbender & Gerpott, 2021; Scheuer *et al.*, 2023; Y. Wang & Shi, 2024). On the digital side, data-driven insight, digital business strategy, absorptive capacity, and platform capability influence whether firms can convert digital investment into ambidextrous innovation outcomes (Kastelli *et al.*, 2022; Lu *et al.*, 2023; Zheng, 2024; Zhu & Li, 2023). Recent studies further show that digital outcomes depend on micro-foundations of DC and knowledge-based reconfiguration processes (Hashem *et al.*, 2024; Kowalski *et al.*, 2024; Mele *et al.*, 2023; Pundziene *et al.*, 2021). Nevertheless, few studies examine whether DT and DigiT become innovation outcomes through a shared behavioral transfer mechanism, or whether this mechanism differs across country contexts. This study is therefore situated within the micro-foundations branch of DC research, with IKT as the routine linking resource conditions to ambidextrous innovation.

1.1. Theoretical foundation

The main theoretical lens of this study is DC theory (Teece *et al.*, 1997), which defines DC as a firm's ability to integrate, build, and reconfigure internal and external resources in changing environments. In this paper, DC are not used as a general label for good management; rather, they serve as an analytical mechanism for explaining how firms sense, seize, and transform demographic and digital changes. Sensing allows firms to detect demographic risks (knowledge loss, age-based fragmentation) and digital opportunities. Seizing reflects resource commitment to digital infrastructure, intergenerational collaboration routines, and knowledge codification systems. Transforming refers to reconfiguring human resource practices, communication norms, and innovation processes so that IKT becomes an institutionalized routine. Under this mechanism, DT and DigiT are antecedent conditions, IKT is the transmission channel, and DC are the boundary condition that determines whether firms can convert these inputs into ambidextrous innovation performance.

The theoretical contribution of the framework lies in separating three roles that are often blended. DT and DigiT are treated as antecedent conditions; IKT is treated as the micro-level behavioral routine through which employees exchange and recombine knowledge; and DC are treated as the firm-level orchestration capability that strengthens or weakens this routine. This separation allows the model to explain why similar demographic or digital conditions can produce different innovation outcomes across firms and countries.

Based on this analytical lens, the study operationalizes four closely related constructs:

- (i) Firm-level DT: The change in a firm's workforce age structure, captured by intergenerational age diversity and workforce aging intensity. Moderate diversity creates complementary combinations of experience-based and digital-native cognition, while excessive aging may increase knowledge obsolescence risk and excessive youth may reduce accumulated domain memory (Parrotta *et al.*, 2014).
- (ii) DigiT: The process by which firms use digital technologies to redesign business processes, organizational architecture, and business models, especially in knowledge management, research and development, and cross-functional collaboration (Gong *et al.*, 2022; Mele *et al.*, 2023).
- (iii) IKT: The two-way transfer of explicit knowledge (manuals, data) and tacit knowledge (experience, operational know-how) between younger and older employees. In the context of demographic change, generation is operationalized through age cohorts but

interpreted behaviorally rather than stereotypically. Older workers are more likely to carry cumulative domain knowledge, relation-specific memory, and quality/risk heuristics; younger workers are more likely to possess digital fluency, rapid experimentation habits, and exposure to emerging customer or technology logics. Middle-career employees can act as translators between these groups. Effective transfer therefore depends on reciprocity, trust, and mutually recognized value in cross-generation collaboration (Burmeister *et al.*, 2020; Fasbender *et al.*, 2021; Fasbender & Gerpott, 2021; Scheuer *et al.*, 2023; Y. Wang & Shi, 2024). Accordingly, the firm-level implications of demographic change are not simply a comparison of age groups. The relevant question is whether the firm has routines that convert cohort-based differences into reciprocal learning. Mentoring, reverse mentoring, mixed-age project teams, digital repositories, and trust-building human resource practices are mechanisms through which individual generational differences become organizational knowledge assets.

- (iv) Ambidextrous innovation performance: The firm's ability to simultaneously achieve exploitative and exploratory innovation and realize balance/synergy between the two. Exploitative innovation relies on refinement and reuse of existing knowledge, whereas exploratory innovation relies on recombination of new knowledge; both require effective intergenerational knowledge integration and organizational ambidexterity routines (Hashem *et al.*, 2024; Ju *et al.*, 2022; Junni *et al.*, 2013).

1.2. Hypotheses development

1.2.1. Main effects on ambidextrous innovation performance

Firm-level DT has a dual impact on ambidextrous innovation. On the one hand, moderate intergenerational age diversity brings complementary knowledge: older employees have rich tacit knowledge of industry rules, operational experience, relational history, and risk control, which supports incremental exploitative innovation; younger employees have cutting-edge digital skills, experimentation orientation, and sensitivity to new market trends, which supports exploratory innovation (Backes-Gellner & Veen, 2012; Mothe & Nguyen-Thi, 2021). The complementarity of intergenerational knowledge can promote a balance in ambidextrous innovation when firms establish routines for mutual learning. On the other hand, excessive aging may increase knowledge obsolescence risk, reduce learning speed, and create succession pressure; excessive youth may reduce accumulated domain memory,

weaken risk screening, and make it difficult to transform novel ideas into commercial value. Strong age polarization may also intensify communication barriers and age stereotypes, which inhibit innovation performance. Therefore, DT is expected to improve ambidextrous innovation up to a point and weaken it beyond that point. Therefore, we propose H1: Firm-level DT has a significant inverted U-shaped effect on ambidextrous innovation performance.

Digital transformation can significantly promote firms' ambidextrous innovation performance. For exploitative innovation, digital technologies such as big data and industrial internet can optimize existing production and operation processes, improve resource allocation efficiency, and realize incremental improvement of products and services (Nambisan *et al.*, 2019). For exploratory innovation, digital technologies such as artificial intelligence and cloud computing can reduce the cost of experimentation, help firms identify new market opportunities, and support the development of new products and new markets. Recent evidence also shows that DigiT improves innovation performance by enhancing knowledge flows, data integration, and capability reconfiguration rather than through technology adoption alone (Chen & Kim, 2023; Gong *et al.*, 2022; Lu *et al.*, 2023; Zheng, 2024). In addition, DigiT can break down organizational silos, promote cross-departmental knowledge sharing, and support the balance and synergy of exploitative and exploratory innovation. Therefore, we propose H2: DigiT has a significant positive effect on firm ambidextrous innovation performance.

1.2.2. Mediating role of intergenerational knowledge transfer

Intergenerational knowledge transfer is the core mechanism by which demographic and DigiTs affect ambidextrous innovation. First, the DT has an inverted U-shaped effect on IKT. Moderate intergenerational diversity creates both demand and opportunity for knowledge transfer: older employees have accumulated experience that is worth transferring, and younger employees have digital and market knowledge that can be transferred in reverse. This reciprocal logic is strongest when age groups are sufficiently represented, and interaction routines exist (Burmeister *et al.*, 2020; Fasbender *et al.*, 2021). However, excessive aging may narrow the recipient base for reverse learning and increase retirement-related knowledge loss, while excessive youth may reduce the stock of deep firm-specific experience available for transfer. Extreme age imbalance may also weaken trust and increase age-based categorization. Therefore, we propose H3a: Firm-level DT has a significant inverted U-shaped effect on IKT.

Second, DigiT can significantly promote IKT. Digital knowledge management systems and collaboration platforms can encode tacit knowledge into reusable, explicit knowledge, reduce the risk of knowledge loss, overcome time-space barriers in intergenerational communication, and improve the absorptive capacity of knowledge recipients (Gong *et al.*, 2022; Mele *et al.*, 2023; Zheng, 2024). Digital tools also enable reverse mentoring because younger employees' platform and data skills can be shared with older employees through visible workflows, dashboards, and collaborative experimentation. Therefore, we propose H3b: DigiT has a significant positive effect on IKT.

Third, IKT can significantly promote ambidextrous innovation performance. The transfer of explicit experience and tacit know-how from older to younger employees can help younger employees quickly master core business capabilities, optimize existing processes, and improve exploitative innovation performance; the reverse transfer of digital knowledge and innovative thinking from younger to older employees can help the firm break path dependence, explore new technologies and markets, and improve exploratory innovation performance (Burmeister *et al.*, 2020; Fasbender & Gerpott, 2021). At the same time, two-way IKT integrates experience-based reliability with digitally enabled experimentation, thereby supporting an ambidextrous balance in innovation. Therefore, we propose H3c: IKT has a significant positive effect on firm ambidextrous innovation performance.

Combining the three sub-hypotheses above, IKT mediates the effects of DT and DigiT on ambidextrous innovation performance. Therefore, we propose: H3: IKT mediates the relationship between firm-level DT, DigiT and ambidextrous innovation performance.

1.2.3. Moderating role of dynamic capabilities

Dynamic capabilities are the core boundary condition of the above mechanisms. Firms with strong DC have stronger sensing capability, which can better identify the value of intergenerational knowledge and the opportunities of DigiT; stronger seizing capability, which can integrate digital resources and intergenerational knowledge to build a formal knowledge transfer system; and stronger transforming capability, which can adjust organizational structure and culture to reduce intergenerational conflicts and reconfigure knowledge resources to adapt to demographic and digital changes (Teece, 2007; C.L. Wang & Ahmed, 2007).

This logic gives DC a specific analytical role. They do not merely add another positive predictor of innovation; they change the efficiency with which firms convert

demographic diversity and digital investment into knowledge-transfer routines. This is why DC are modeled as a moderator and as the source of moderated mediation.

For the inverted U-shaped relationship between DT and IKT, firms with strong DC can maximize the knowledge complementarity of moderate intergenerational diversity, and alleviate the negative impact of excessive aging or youth on knowledge transfer through organizational process reconfiguration. Therefore, we propose H4: DC positively moderate the inverted U-shaped relationship between firm-level DT and IKT.

For the positive relationship between DigiT and IKT, firms with strong DC can better integrate digital technologies throughout the knowledge management process, translate digital technology investments into effective knowledge-transfer capabilities, and amplify DigiT's promotional effect on IKT. Therefore, we propose H5: DC positively moderate the relationship between DigiT and IKT.

Furthermore, DC will moderate the indirect effects of DT and DigiT on ambidextrous innovation via IKT. Firms with stronger DC will have a more significant mediating effect of IKT. Therefore, we propose H6: DC moderates the indirect effects of firm-level DT and DigiT on ambidextrous innovation performance via IKT.

2. Data and methods

2.1. Data and sample

This study used firm-level data from the WBES (2019–2023). To ensure cross-country comparability, we retained 32 countries in which the core modules on workforce structure, digital practices, knowledge management, and innovation were simultaneously available, and we harmonized coding rules before estimation. WBES applies standardized questionnaires, unified field protocols, and stratified sampling by firm size, industry, and location, which improves comparability while preserving firm-level variation. The retained sample includes firms from manufacturing and service sectors because both sectors face demographic knowledge-loss risks and DigiT pressures, but they differ in knowledge codification, production routines, and innovation cycles.

Sample screening followed both data-quality and theoretical criteria: (i) observations with missing values were removed for core constructs; (ii) firms younger than three years were excluded, because early-stage firms have unstable routines and incomplete knowledge-transfer systems; and (iii) logically abnormal records (e.g., negative employees, implausible research and development ratios) were excluded. The final sample included 12,468 firms

from 32 countries across manufacturing and services, ranging from micro to large firms and spanning both developed and emerging economies. This structure is suitable for testing whether antecedents of DC operate at the firm level across heterogeneous country contexts, while still requiring explicit controls for firm-, industry-, and country-level differences.

Since the unit of analysis is the firm, company-specific characteristics were addressed at two levels. First, the sampling design and controls accounted for observable firm heterogeneity, including size, age, ownership, research and development intensity, export intensity, and sector. Second, country-specific characteristics were treated as contextual conditions rather than ignored: all baseline models included country fixed effects, standard errors were clustered by country, and the robustness section reported developed versus emerging economy sub-samples. These steps do not make firms from 32 countries identical, but they reduce confounding from stable national differences and allow the analysis to focus on within-country firm-level variation.

2.2. Variable measurement

All variables were measured using established scales from prior studies and standard WBES question items to support measurement reliability and validity. All Likert scales used a five-point rating (1 = not at all, 5 = to a very great extent).

2.2.1. Dependent variable

Following established measures from He & Wong (2004) and Cao *et al.* (2009), ambidextrous innovation performance (AIP) was measured using the balance of exploitative innovation (EI) and exploratory innovation (ERI). EI was measured by three items: (i) the degree of improvement of existing products/services; (ii) the degree of optimization of existing production/service processes; and (iii) the degree of efficiency improvement of existing supply chains. ERI was measured by three items: (i) the degree of launching brand-new products/services; (ii) the degree of entering brand new markets/industries; and (iii) the degree of adopting brand new production/service technologies. Cronbach's α for the scale was 0.872. The core AIP was measured by the product term of EI and ERI (to reflect the balance of ambidexterity), and the sum term of EI and ERI was used for robustness tests.

2.2.2. Independent variables

Demographic transition was measured using two dimensions synthesized by exploratory factor analysis (EFA). Intergenerational age diversity was calculated by the Blau index; employees were divided into five age cohorts: <25 years old, 25–34 years old, 35–44 years old, 45–54

years old, and ≥ 55 years old; Blau index = $1 - \sum(p_i)^2$, where p_i is the proportion of employees in group i . Firm aging intensity was measured as the proportion of employees aged ≥ 55 among all employees. The Kaiser–Meyer–Olkin (KMO) value of EFA was 0.743, Bartlett’s test was significant at $p < 0.001$, and Cronbach’s α was 0.781.

Digital transformation was measured using four items: (i) the extent to which digital technologies (big data, artificial intelligence, cloud computing) are used in operations; (ii) the extent to which digital platforms are used for internal communication and knowledge management; (iii) the extent to which digital technologies are used for research and development and innovation activities; and (iv) the overall level of investment in DigiT. The KMO value of EFA was 0.812, Bartlett’s test was significant at $p < 0.001$, and Cronbach’s α was 0.864.

The mediating variable, IKT, was measured using four items adapted from the IKT literature (Burmeister *et al.*, 2020; Wang & Shi, 2024): (i) the degree of explicit knowledge sharing (work manuals, process specifications) between intergenerational employees; (ii) the degree of tacit knowledge transfer (work experience, know-how) between intergenerational employees; (iii) the implementation of a formal mentoring system for senior employees to transfer knowledge to new employees; and (iv) the implementation of a reverse mentoring system for young employees to transfer digital knowledge to senior employees. The KMO value of EFA was 0.795, Bartlett’s test was significant at $p < 0.001$, and Cronbach’s α was 0.853.

2.2.3. Moderating variable

Based on Teece *et al.* (1997) and C.L. Wang & Ahmed (2007), DC was measured using six items covering three dimensions: (i) sensing capability: the ability to identify market opportunities/technology trends, and the ability to collect and analyze internal and external information; (ii) seizing capability: the ability to integrate resources to develop new products/services, and the ability to transform innovation opportunities into commercial value; and (iii) transforming capability: the ability to adjust organizational structure/processes to adapt to changes, and the ability to reconfigure internal and external knowledge resources. The KMO value of EFA was 0.836, Bartlett’s test was significant at $p < 0.001$, and Cronbach’s α was 0.887.

2.2.4. Control variables

To reduce confounding from other factors, we included control variables widely used in existing research: firm size (natural logarithm of total employees), firm age (natural logarithm of establishment years), ownership (state-owned = 1, non-state-owned = 0), research and development

intensity (research and development expenditure/total revenue), export intensity (export revenue/total revenue), industry fixed effects or sector indicators, and country fixed effects. These controls account for observable firm resources, organizational maturity, market exposure, industry structure, and stable national institutional and economic differences.

2.3. Data analysis

We used SPSS 26.0 and Stata 17.0 and followed a theory-to-model sequence: (i) descriptive statistics, correlations, and multicollinearity checks (variance inflation factor); (2) reliability and validity tests (Cronbach’s alpha, confirmatory factor analysis, composite reliability, and average variance extracted); (iii) hierarchical regressions for linear and quadratic main effects, mediation paths, and moderation effects; and (iv) Hayes PROCESS (Model 4 and Model 8) with 5,000 bootstrap resamples for indirect and moderated-indirect effects. Hierarchical regression is appropriate because the hypotheses were nested, with each block corresponding to a theoretical mechanism: controls, antecedents, mediator, moderator, and interaction terms. Because the data were nested within countries, the baseline regressions were not treated as simple pooled ordinary least squares (OLS); country fixed effects, industry fixed effects, or sector indicators, and heteroskedasticity-robust standard errors clustered at the country level were included where applicable. Robustness tests included alternative dependent-variable measures, two-stage least squares instrumental-variable estimation, developed- and emerging-economy subsample estimation, industry- and country-structure checks, and lag-effect tests.

3. Results

3.1. Descriptive statistics and correlation analysis

Table 1 reports the descriptive statistics and correlation coefficients of all variables. The mean values of AIP, DT, DigiT, and IKT are 3.012 (standard deviation [SD] = 0.947), 0.324 (SD = 0.152), 3.118 (SD = 0.869), and 2.887 (SD = 0.918), respectively. The correlation coefficients indicate that DT is significantly positively correlated with AIP ($r = 0.121$, $p < 0.01$), DigiT is significantly positively correlated with AIP ($r = 0.382$, $p < 0.001$), and IKT is significantly positively correlated with AIP ($r = 0.419$, $p < 0.001$), consistent with our theoretical expectations. All variance inflation factor values are between 1.02 and 2.35, well below the critical value of 5, indicating no serious multicollinearity.

3.2. Reliability and validity test

The reliability results show that for all the constructs,

Table 1. Descriptive statistics and correlation matrix

Variable	Mean	SD	AIP	DT	DigiT	IKT	DC	Firm size	Firm age	Ownership	Industry	R&D intensity	Export intensity
AIP	3.012	0.947	1.000										
DT	0.324	0.152	0.121**	1.000									
DigiT	3.118	0.869	0.382***	0.087*	1.000								
IKT	2.887	0.918	0.419***	0.105**	0.394***	1.000							
DC	3.054	0.892	0.403***	0.093*	0.426***	0.451***	1.000						
Firm size	4.287	1.325	0.214***	0.132***	0.287***	0.198***	0.225***	1.000					
Firm age	2.563	0.784	0.064*	0.201***	0.058	0.072*	0.081*	0.312***	1.000				
Ownership	0.124	0.329	0.032	0.057	0.041	0.028	0.035	0.246***	0.187***	1.000			
Industry	0.587	0.492	0.102**	0.063*	0.114**	0.089*	0.095*	0.178***	0.062	0.054	1.000		
R&D intensity	0.087	0.103	0.325***	0.048	0.301***	0.287***	0.294***	0.165***	0.037	0.029	0.086*	1.000	
Export intensity	0.214	0.286	0.157***	0.059	0.142***	0.103**	0.118**	0.223***	0.071*	0.046	0.195***	0.124**	1.000

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; $N = 1,2468$.

Abbreviations: AIP: Ambidextrous innovation performance; DC: Dynamic capabilities; DigiT: Digital transformation; DT: Demographic transition; IKT: Intergenerational knowledge transfer; R&D: Research and development; SD: Standard deviation.

Cronbach's alpha is greater than 0.75, composite reliability is greater than 0.80, and average variance extracted is greater than 0.55, supporting good reliability and convergent validity of the scales. Confirmatory factor analysis results indicate that the four-factor model (DT, DigiT, IKT, DC) fits the data well (comparative fit index = 0.941, Tucker–Lewis Index = 0.927, root mean square error of approximation = 0.051), and is significantly better than the single-factor model, supporting discriminant validity and reducing common-method concerns. To address cross-country comparability, constructs were harmonized using the same WBES item definitions and standardized before creating interaction terms. Nevertheless, DigiT is measured as adoption/intensity rather than full digital maturity, and ambidextrous innovation is based on reported exploitative and exploratory innovation indicators. These measurement constraints are acknowledged in the limitations and partially addressed through alternative AIP measurement in robustness tests.

3.3. Hypothesis testing

3.3.1. Main effect test

The results of the hierarchical regression analyses for the main effects are summarized in Table 2. Model 1 includes only the controls, whereas Model 2 also includes DT, its quadratic term, and DigiT. The coefficient of DT is significantly positive ($\beta = 0.218, p < 0.001$), and the coefficient of the DT squared term is significantly negative ($\beta = -0.187, p < 0.001$), indicating that DT has a significant inverted U-shaped effect on AIP, supporting H1. The coefficient of DigiT is significantly positive ($\beta = 0.324, p < 0.001$), indicating that DigiT has a significant positive effect on AIP, supporting H2.

3.3.2. Mediating effect test

Model 3 in Table 2 uses IKT as the dependent variable. The results show that the coefficient of DT is significantly positive ($\beta = 0.242, p < 0.001$), while the coefficient of the DT squared term is significantly negative ($\beta = -0.203, p < 0.001$), supporting H3a; the coefficient of DigiT is significantly positive ($\beta = 0.357, p < 0.001$), supporting H3b. When Model 4 adds IKT to Model 2, the coefficient of IKT becomes significantly positive ($\beta = 0.386, p < 0.001$), supporting H3c. Meanwhile, the coefficients of DT, the DT squared term, and DigiT remain significant but smaller in absolute value than those in Model 2, indicating that IKT plays a partial mediating role.

The bootstrapped test with 5,000 resamples shows that the indirect effect of DT on AIP via IKT is 0.064, with a 95% confidence interval of 0.042–0.098, which excludes zero and is therefore significant; the indirect effect of DigiT on AIP via IKT is 0.138, with a 95% confidence interval of 0.102–0.167, which excludes zero and is therefore significant. Thus, H3 is fully supported.

3.3.3. Moderating effect test

Table 3 reports the results of the moderating effect test. Model 5 uses IKT as the dependent variable and includes DC and the interaction terms $DT \times DC$, $DT^2 \times DC$, and $DigiT \times DC$. The results show that the coefficient of $DT^2 \times DC$ is significantly positive ($\beta = 0.124, p < 0.01$), indicating that DC positively moderates the inverted U-shaped relationship between DT and IKT, supporting H4. Simple slope analysis shows that for firms with high DC (mean +1 SD), the inverted U-shaped curve has a higher inflexion point and a wider range of positive effects; for firms with low DC (mean –1 SD), the curve is steeper, and the negative effect appears earlier.

Table 2. Hierarchical regression results of main and mediating effects

Variables	Model 1 (AIP)	Model 2 (AIP)	Model 3 (IKT)	Model 4 (AIP)
Control variables	Included	Included	Included	Included
DT	-	0.218***	0.242***	0.135**
DT ²	-	-0.187***	-0.203***	-0.109**
DigiT	-	0.324***	0.357***	0.189***
IKT	-	-	-	0.386***
R ²	0.142	0.287	0.265	0.384
F-value	28.74***	47.21***	42.68***	65.39***
ΔR^2	-	0.145***	0.123***	0.097***

Notes: ** $p < 0.01$, *** $p < 0.001$; standardized coefficients are reported.

Abbreviations: AIP: Ambidextrous innovation performance; DigiT: Digital transformation; DT: Demographic transition; IKT: Intergenerational knowledge transfer.

The coefficient of DigiT $\times$ DC is significantly positive ($\beta = 0.158$, $p < 0.001$), indicating that DC positively moderates the positive relationship between DigiT and IKT, supporting H5. Simple slope analysis shows that the slope of DigiT is 0.421 ($p < 0.001$) for high-DC firms and 0.213 ($p < 0.01$) for low-DC firms, with a significant difference between the two groups.

Table 3. Moderating effect regression results

Variables	Model 5 (IKT)
Control variables	Included
DT	0.231***
DT ²	-0.198***
DigiT	0.342***
DC	0.286***
DT $\times$ DC	0.082*
DT ² $\times$ DC	0.124**
DigiT $\times$ DC	0.158***
R ²	0.352
F-value	51.47***
ΔR^2	0.087***

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; standardized coefficients are reported.

Abbreviations: DigiT: Digital transformation; DC: Dynamic capabilities; DT: Demographic transition; IKT: Intergenerational knowledge transfer.

3.3.4. Moderated mediating effect test

The bootstrapped test with 5,000 resamples (PROCESS Model 8) shows that for high-DC firms, the indirect effect of DT on AIP via IKT is 0.087, with a 95% CI of 0.053–0.124, which excludes zero and is therefore significant; the indirect effect of DigiT is 0.178, with a 95% CI of 0.132–0.225, which excludes zero and is therefore significant. For low-DC firms, the indirect effect of DT is 0.032, with a 95% CI of -0.004–0.068, including zero and therefore insignificant; the indirect effect of DigiT is 0.089, with a 95% CI of 0.041–0.137, which excludes zero and is therefore significant, but the effect size is much smaller than that for high-DC firms. Thus, H6 is supported.

3.4. Robustness tests

To evaluate validity and robustness, we conducted complementary checks focusing on measurement substitution, potential endogeneity, cross-country heterogeneity, industry and country structure, and temporal ordering.

3.4.1. Replacement of dependent variable measurement

We replaced the product terms of EI and ERI with a sum term as the measure of AIP, and re-estimated all regression models. The results show that the signs and significance levels of all core variable coefficients are consistent with the baseline regression, indicating that the findings are stable.

3.4.2. Endogeneity treatment with instrumental variables

To mitigate reverse causality (e.g., highly innovative firms may invest more in digitalization and knowledge transfer), we used two country-level instruments: (i) national digital infrastructure penetration rate for DigiT; and (ii) national aging rate from population statistics for DT. First-stage F statistics are above 10, reducing weak-instrument concerns. In the second stage, key coefficient signs and significance remain consistent with baseline results. However, these instruments are not interpreted as definitive proof of causality because country-level digital infrastructure and aging may also be associated with broader institutional conditions. We therefore treated the instrumental variables results as a sensitivity analysis that reduces, but did not fully eliminate, endogeneity concerns.

3.4.3. Subsample test

We split the sample into developed economies (6,217 firms) and emerging economies (6,251 firms). All hypotheses remain supported in both groups, but effect sizes differ: the DigiT effect is stronger in emerging economies, where digital infrastructure gaps make firm-level digital investment more salient, while the demographic-diversity effect is stronger in developed economies, where workforce aging pressure is more visible. This supports external validity and indicates meaningful country-context heterogeneity.

3.4.4. Lag-effect test

We used 2019 WBES indicators as antecedents and 2022 follow-up outcomes (4,213 balanced-panel firms) to test temporal ordering. Core coefficients remain significant and directionally consistent with the baseline model, providing additional support against simple reverse-causality explanations. Because the panel window is still limited, these results are interpreted as evidence of temporal robustness rather than as a complete causal identification strategy.

3.4.5. Industry and country-structure checks

We re-estimated the baseline models after adding sector fixed effects and after clustering standard errors at the country level. The core signs and significance levels

remained stable. These checks indicate that the findings are not driven solely by a single industry group or by unmodeled country-level error correlation, although they do not substitute for a full multilevel causal design.

4. Discussion

Drawing on DC theory, this study shows that DT and DigiT affect ambidextrous innovation through a conversion process rather than through a simple direct resource effect. DT changes the mix of experience-based knowledge, market memory, risk heuristics, digital familiarity, and learning orientation inside the firm. DigiT changes the media through which this knowledge is codified, searched, shared, and recombined. IKT is therefore the behavioral mechanism that converts demographic and digital conditions into exploitative and exploratory innovation, while DC determine how effectively managers sense these conditions, seize knowledge-transfer opportunities, and transform temporary exchanges into stable routines (Teece, 2007; Teece *et al.*, 1997; C.L. Wang & Ahmed, 2007).

For H1, the inverted U-shaped effect of DT can be explained by the balance between knowledge complementarity and coordination cost. At moderate levels of age diversity, older employees contribute tacit process knowledge, customer and supplier relationships, quality-control experience, and risk judgment, whereas younger employees contribute digital skills, awareness of external technologies, and a willingness to experiment. This combination supports exploitation by improving existing processes and supports exploration by broadening the search for new solutions (Backes-Gellner & Veen, 2012; Mothe & Nguyen-Thi, 2021). When DT becomes too strong, or the age structure becomes highly imbalanced, however, the same diversity may create social categorization, communication barriers, stereotype threat, and slower consensus formation; knowledge becomes segmented by cohort, and the firm loses the coordination capacity needed for ambidextrous innovation. For H2, DigiT improves ambidextrous innovation because digital platforms, data systems, and collaborative tools reduce knowledge-search costs, make tacit experience more visible, accelerate feedback from customers and operations, and allow exploratory experiments to be linked with exploitative process improvement rather than remaining isolated technology projects (Chen & Kim, 2023; Gong *et al.*, 2022; Li *et al.*, 2024; Lu *et al.*, 2023; Nambisan *et al.*, 2019; Zheng, 2024).

For H3a–H3c, IKT explains why these antecedents influence innovation. The DT effect on transfer is also nonlinear: moderate age diversity creates reciprocal learning needs, but excessive generational separation

weakens trust and willingness to exchange knowledge (Burmeister *et al.*, 2020; Fasbender *et al.*, 2021; Fasbender & Gerpott, 2021; Scheuer *et al.*, 2023; Y. Wang & Shi, 2024). DigiT strengthens transfer by providing shared repositories, digital traces, remote collaboration channels, and data-based boundary objects that help senior and junior employees translate different forms of knowledge into a common problem-solving language (Gong *et al.*, 2022; Mele *et al.*, 2023; Sánchez Ramírez *et al.*, 2022; Zheng, 2024). Once such transfer occurs, exploitative innovation benefits from the preservation and refinement of accumulated know-how, while exploratory innovation benefits from recombining legacy knowledge with digital experimentation (Hashem *et al.*, 2024; Ju *et al.*, 2022; Qi *et al.*, 2024). H4–H6 further show that DC amplify these mechanisms: sensing routines identify which generational knowledge is strategically valuable, seizing routines allocate resources to mentoring, reverse mentoring, and digital knowledge platforms, and transforming routines embed the exchanged knowledge into new processes, roles, and innovation projects (Abdurrahman *et al.*, 2024; Al-Moaid & Almarhdi, 2024; Chang *et al.*, 2024; Dobrovnik *et al.*, 2025; Held *et al.*, 2025; Iden & Bygstad, 2024; Khattak *et al.*, 2025; Kowalski *et al.*, 2024; Secundo *et al.*, 2025; Valdez-Juárez *et al.*, 2024). Country context qualifies the strength of these mechanisms. In developed economies, aging pressure and formal employment systems make demographic knowledge transfer more salient; in emerging economies, digital infrastructure gaps make firm-level digital investment and capability building especially important for converting knowledge transfer into innovation performance.

This study makes three main theoretical contributions. First, this study refines DT research by showing that firm-level age structure affects innovation nonlinearly and by clarifying the underlying mechanism of knowledge complementarity versus coordination costs. Second, it links DigiT to ambidextrous innovation through an explicit behavioral pathway of IKT, extending knowledge-based explanations of digital outcomes beyond technology adoption itself. Third, it advances DC research by specifying IKT as a micro-foundation and by testing how sensing, seizing, and transforming capabilities condition demographic and digital antecedents under heterogeneous country settings. The contribution is therefore a more precise explanation of the mechanism and boundary conditions, not a claim that the study resolves all controversies in the innovation or DC literature.

This study provides actionable practical guidance for firm managers. Managerial implications follow directly from the supported hypotheses. First, H1 implies that firms

should actively manage their age structure rather than simply increase or decrease the share of any generation: recruitment, succession planning, phased retirement, and mixed-age project assignment should be designed to keep experience-based and digital-native knowledge in productive balance. Second, H2 implies that DigiT should prioritize knowledge architecture, including digital repositories, collaborative platforms, data dashboards, and process transparency that make knowledge easier to codify and recombine. Third, H3 implies that firms should implement generation-specific collaboration routines: senior experts can lead context-rich mentoring, quality review, and customer-history interpretation, while younger employees can lead reverse mentoring, digital experimentation, and rapid prototyping; both groups should share accountability for innovation outcomes. Fourth, H4–H6 imply that capability development is important because digital tools and demographic diversity produce stronger returns only when managers build sensing routines (opportunity/risk scanning), seizing routines (resource orchestration and investment), and transforming routines (process redesign and cultural integration). At the policy level, governments and industry associations can support firm-level implementation by improving digital infrastructure, lifelong learning systems, age-inclusive employment policies, and cross-generational training programs, but the conversion of these national-level conditions into innovation still depends on firm-level DC.

This study has several limitations. First, despite lag tests and instrumental variable estimation, most analyses remain observational; future research should use longer panels, natural experiments, or quasi-experimental designs to strengthen causal identification. Second, the instrumental variable strategy is useful as a robustness check but not fully conclusive, because country-level instruments may affect firm innovation through broader institutional channels. Third, measurement validity can be improved, especially for DigiT and ambidextrous innovation, by combining survey measures with objective digital trace, patent, new product, or process performance indicators. Fourth, cross-country comparability may still be affected by unobserved institutional, cultural, and labor-market differences even after fixed effects and clustered errors; future studies can use explicit multilevel models and country-level moderators such as labor regulation, education systems, and digital infrastructure quality. Fifth, generation is proxied by age structure; future research should directly measure value orientation, cognitive style, digital skill, age stereotypes, intergenerational trust, and motivation to unpack behavioral micro-mechanisms in greater depth.

5. Conclusion

This paper examines how firm-level DT and DigiT relate to ambidextrous innovation performance, and tests the mediating role of IKT and the moderating role of DC using multi-country WBES data. Results show an inverted U-shaped demographic effect, a positive DigiT effect, significant mediation through IKT, and stronger mechanisms at higher DC. These findings provide a mechanism-based explanation of how demographic and digital shifts are translated into firm innovation outcomes through generation-specific knowledge behavior and firm-level capability orchestration. The conclusions should be interpreted with appropriate caution regarding causality and cross-country measurement comparability, but they offer actionable guidance for firms and policymakers seeking sustainable innovation under population aging and digital transition.

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Conflict of interest

The authors declare that they have no competing interests.

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Availability of data

Data will be made available upon reasonable request to the corresponding author.

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