

Article

Digital Capabilities, Green Innovation, and Firm Competitiveness: Evidence from European Firms Using PLS-SEM and Necessary Condition Analysis

Sayyed Khawar Abbas ¹, Zeeshan Arshad ^{2,*}, Celeste Varum ³, Margarita Robaina ³
and Muzzammil Hussain ^{4,5}

¹ Institute of Data Analytics and Information Systems, Department of Information Systems, Corvinus University of Budapest, 8 Fovam Ter, 1093 Budapest, Hungary; sayyedkhawar.abbas@uni-corvinus.hu

² CESAM—Centre for Environmental and Marine Studies, Department of Environment and Planning, University of Aveiro, 3810-193 Aveiro, Portugal

³ GOVCOPP—Research Unit on Governance, Competitiveness and Public Policies, DEGEIT—Department of Economics, Management, Industrial Engineering and Tourism, University of Aveiro, Campus de Santiago, 3810-193 Aveiro, Portugal; camorim@ua.pt (C.V.); mrobaina@ua.pt (M.R.)

⁴ Commerce Department, University of Gujrat, Gujrat 50700, Pakistan; muzzammil.hussain@uog.edu.pk

⁵ Interdisciplinary Research Centre for Finance and Digital Economy, KFUPM Business School, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia

* Correspondence: arshad@ua.pt

Abstract

This study examines whether digital capabilities constitute a necessary condition for green innovation and firm competitiveness in the context of increasing sustainability and digital transformation pressures. Although prior research frequently links digitalization to improved environmental and business outcomes, limited evidence exists on whether firms must achieve a minimum level of digital capability to successfully generate green innovation and sustain competitive performance. To address this gap, the study investigates the relationships among digital capabilities, green innovation, and firm competitiveness using Partial Least Squares Structural Equation Modelling (PLS-SEM) and Necessary Condition Analysis (NCA). Using survey data from 740 firms across Hungary, Romania, Poland, Austria, and other Central and Eastern European (CEE) countries, the findings demonstrate that digital capabilities significantly enhance both green innovation and firm competitiveness. Green innovation further acts as a mediating mechanism through which digital capabilities translate into superior competitive outcomes. Importantly, the NCA results reveal that digital capabilities are not merely beneficial but represent a necessary condition for achieving high levels of green innovation and competitiveness within the studied sample of CEE firms, suggesting a threshold relationship that warrants further causal investigation. Firms with higher digital maturity consistently outperform less digitally developed firms in leveraging sustainability-oriented innovation strategies. The study contributes to the literature by advancing understanding of how digital transformation capabilities support sustainable competitiveness and by combining sufficiency and necessity analytical approaches to examine these relationships. The findings also provide practical implications for managers and policymakers by highlighting the strategic importance of investing in digital capabilities to simultaneously support environmental sustainability and long-term competitive performance.



Academic Editor: Colin Michael Hall

Received: 22 May 2026

Revised: 6 June 2026

Accepted: 11 June 2026

Published: 17 June 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article

distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

Keywords: digital capabilities; green innovation; firm competitiveness; digital transformation; PLS-SEM; necessary condition analysis; artificial intelligence; Internet of Things; big data analytics; central and eastern Europe; sustainability transition

1. Introduction

European firms are increasingly operating within a competitive environment shaped by two interrelated transformations: the rapid diffusion of digital technologies and the intensifying transition toward environmental sustainability. This dual process, often referred to as the “twin transition,” is redefining how firms create value, innovate, and sustain competitive advantage. Digital technologies such as the Internet of Things (IoT), big data analytics, artificial intelligence (AI), and cloud computing enable firms to improve operational efficiency, enhance decision-making, redesign business models, and develop more responsive innovation processes [1,2]. At the same time, the European sustainability agenda, driven by policy instruments such as the European Green Deal, the Corporate Sustainability Reporting Directive (CSRD), the EU Taxonomy for Sustainable Finance, and the Carbon Border Adjustment Mechanism (CBAM), has increased the strategic importance of green innovation [3–5]. As a result, environmental innovation is no longer a voluntary activity pursued mainly for reputational benefits; rather, it has become a critical condition for regulatory compliance, market legitimacy, and long-term competitiveness [3–5].

Although the relationship between digital transformation and sustainability has attracted growing scholarly attention, important questions remain unresolved. Existing research has shown that digital technologies can support environmental performance and innovation; however, less is known about how broader digital capability portfolios translate into green innovation and competitive outcomes [6–8]. In particular, prior studies have often examined whether digital capabilities are sufficient to improve performance, while paying less attention to whether firms must achieve minimum levels of digital capability before high levels of green innovation and competitiveness become possible [6,7]. This distinction is important because firms may not benefit equally from digital transformation if their capabilities remain below the threshold required to support sustainability-oriented innovation.

A further limitation in the existing literature is the limited integration of digital maturity perspectives with green innovation and firm competitiveness. While some firms may act as digital leaders with advanced technology portfolios, others remain digital intermediates or laggards. Yet it remains unclear whether digital leadership is a prerequisite for achieving green competitive advantage or whether alternative capability configurations can produce similar outcomes [8]. This issue is especially relevant in Central and Eastern European economies, where firms face the pressures of the European twin transition while often operating under distinct structural conditions, including lower average technology investment capacity, uneven institutional support, and varying levels of sustainability readiness [9,10].

Against this background, the present study investigates how digital capabilities influence green innovation and firm competitiveness among European firms, with particular attention to the Central and Eastern European context. The central research question guiding this study is: To what extent do digital capabilities enable green innovation and firm competitiveness, and what minimum levels of digital capability are required to achieve high-performance outcomes? By addressing this question, the study responds to the need for a clearer understanding of the mechanisms linking digital transformation, sustainability-oriented innovation, and competitive advantage.

This study addresses these gaps through a research design that integrates three complementary analytical approaches. PLS-SEM tests the sufficiency pathways posited in the four hypotheses, K-means cluster analysis identifies empirically grounded digital maturity typologies, and Necessary Condition Analysis (NCA) establishes the necessary condition thresholds for green innovation and competitive performance, answering the question of how much digital capability is enough to unlock each level of outcome. Together, these methods provide a more complete picture of the digital–green competitive nexus that any single method could achieve alone.

This study makes several contributions. First, it advances the literature on the twin transition by explaining how a portfolio of digital capabilities, including IoT, big data analytics, AI, and cloud/platform technologies, supports green innovation and firm competitiveness [1,2,6]. Second, it contributes to the capability-based view of competitive advantage by showing that digital capabilities are not only performance-enhancing resources but may also represent enabling conditions for high-level green and competitive outcomes [7,8]. Third, it provides large-sample empirical evidence from an underrepresented European region, thereby extending current knowledge beyond the Western European and advanced-economy contexts that dominate much of the existing literature [9,10]. Finally, the study offers practical guidance for managers and policymakers by identifying the digital capability levels that firms may need to develop in order to successfully navigate the twin transition [6,7].

The paper proceeds as follows. Section 2 develops the theoretical framework and hypotheses. Section 3 describes the methodology. Section 4 presents the results across measurement model, cluster analysis, PLS-SEM structural model, and NCA. Section 5 discusses findings and implications. Section 6 concludes with limitations and future research directions.

2. Theoretical Framework and Hypotheses

2.1. Digital Capabilities and Green Innovation

The concept of digital capabilities has evolved considerably since Bharadwaj et al. [11] first proposed digital business strategy as a distinct theoretical domain. Recent scholarship has converged on a view of digital capabilities as a dynamic, portfolio-level resource that encompasses not just individual technology deployments but the organizational routines, data architectures, and talent configurations that allow firms to deploy technologies purposefully and adaptively [1,2,12]. Drawing on the resource-based view [13] and the dynamic capabilities framework [14], digital capabilities are understood here as higher-order capabilities that enable firms to sense environmental shifts, seize technological opportunities, and reconfigure their operational and innovation processes in response.

Green innovation has been defined as innovations in products, processes, and management practices that reduce environmental burden while improving resource and energy efficiency [15,16].

The theoretical mechanism connecting digital capabilities to green innovation has been elaborated in recent scholarship through two distinct but complementary channels. The first is the information channel: digital technologies lower the cost and increase the precision of environmental monitoring, enabling firms to detect resource inefficiencies, quantify environmental impacts, and identify green innovation opportunities that would otherwise remain invisible [17]. The second is the innovation acceleration channel: AI and analytics capabilities compress the green innovation cycle by enabling computational simulation of environmental consequences before physical investments are committed, reducing both time and financial risk in green product and process development [1,2].

2.2. Hypothesis Development

The digital capabilities can be understood as higher-order organizational capabilities that enable firms to collect, process, integrate, and apply digital information across business functions. From the perspective of the resource-based view and dynamic capabilities theory, such capabilities are valuable because they allow firms to sense environmental changes, seize emerging opportunities, and reconfigure internal resources in response to market and regulatory pressures [13,14]. In the context of the twin transition, digital capabilities are particularly important because green innovation requires firms to identify environmental inefficiencies, redesign products and processes, and coordinate sustainability-oriented changes across organizational boundaries.

The relationship between digital capabilities and green innovation can be explained through several mechanisms. First, digital technologies strengthen environmental sensing. IoT systems and connected devices allow firms to monitor energy consumption, material flows, emissions, waste generation, and equipment performance in real time. This improves the visibility of environmental problems that may otherwise remain hidden in conventional production and management systems [17]. Second, big data analytics and AI improve interpretation and decision-making by transforming large volumes of operational and environmental data into actionable insights. These insights help firms identify where resource use can be reduced, where processes can be redesigned, and where cleaner technologies can be introduced.

Third, digital capabilities accelerate experimentation and innovation. AI-based modelling, simulation tools, and advanced analytics allow firms to test alternative product designs, production processes, and resource configurations before committing to costly physical investments [2]. This reduces uncertainty and lowers the cost of green innovation. Fourth, cloud and platform technologies facilitate cross-functional and inter-organizational collaboration, enabling firms to coordinate sustainability-related knowledge among suppliers, customers, managers, and technical teams [1,2]. Therefore, digital capabilities do not merely support isolated technological improvements; they create an integrated information and coordination infrastructure that enables firms to develop green products, green processes, and green management practices.

H1. Digital Capabilities Predict Green Innovation.

Moreover, recent empirical studies using PLS-SEM in Chinese [18], South Asian [19], and European contexts [20] and Alnor et al. [21] have found positive and significant effects of digital technologies on various dimensions of green innovation.

Accordingly, firms with stronger portfolios of digital capabilities are more likely to detect environmental opportunities, reduce innovation uncertainty, and implement sustainability-oriented changes effectively. Therefore, the following hypothesis is proposed:

H1. Digital capabilities positively and significantly predict green innovation ($\beta > 0$, $p < 0.001$).

H2. Green Innovation Predicts Firm Competitiveness.

Green innovation contributes to firm competitiveness by enabling firms to respond simultaneously to environmental pressures, market expectations, and efficiency demands. Green innovation includes product, process, and management innovations that reduce environmental burden while improving resource and energy efficiency [15,16]. Such innovations can create competitive advantage through both cost-based and differentiation-based mechanisms.

Green innovation also has a regulatory and institutional value. Under the European Green Deal, CSRD, EU Taxonomy, and CBAM, firms face growing pressure to demonstrate environmental responsibility and measurable sustainability performance [3–5]. Firms that develop stronger green innovation capabilities are better positioned to comply with these requirements, reduce regulatory risk, and maintain legitimacy in European markets. In addition, green innovation may improve access to ESG-linked capital, public procurement opportunities, and sustainability-oriented supply chains [22].

Thus, green innovation strengthens competitiveness not only by improving environmental performance but also by supporting market differentiation, cost efficiency, regulatory readiness, and strategic legitimacy. Therefore, the following hypothesis is proposed: markets [22].

H2. *Green innovation positively and significantly predicts firm competitiveness ($\beta > 0$, $p < 0.001$).*

H3. *Direct Effect of Digital Capabilities on Competitiveness.*

Although digital capabilities can enhance competitiveness indirectly through green innovation, they may also produce direct competitive effects. Digital capabilities improve how firms collect information, coordinate resources, automate processes, and respond to customer and market changes. From the dynamic capabilities perspective, firms that can use digital technologies to sense, seize, and reconfigure opportunities are more likely to develop superior competitive positions [14].

Digital capabilities directly enhance competitiveness in several ways. First, they improve operational efficiency by enabling automation, predictive maintenance, real-time monitoring, and data-driven process optimization. These improvements can reduce costs, improve productivity, and increase reliability. Second, digital capabilities strengthen market responsiveness. Big data analytics and AI allow firms to analyze customer behavior, forecast demand, personalize offerings, and respond more quickly to changing market conditions [1,2]. Third, cloud and platform technologies enable scalable business models, digital collaboration, and faster innovation cycles. These capabilities allow firms to enter new markets, improve service delivery, and build more flexible organizational structures.

Importantly, these benefits are not limited to environmental innovation. Even when green innovation is considered separately, digital capabilities may still improve competitiveness through productivity gains, customer responsiveness, innovation speed, and business model renewal. Therefore, digital capabilities are expected to exert a direct effect on firm competitiveness in addition to their indirect effect through green innovation.

Accordingly, the following hypothesis is proposed:

H3. *Digital capabilities positively and significantly predict firm competitiveness directly, net of green innovation.*

H4. *Mediation by Green Innovation.*

The relationship between digital capabilities and firm competitiveness is also likely to operate through green innovation. Digital capabilities provide the informational, analytical, and coordination foundations required for sustainability-oriented innovation, but these capabilities do not automatically translate into competitive advantage. To generate competitive value, digital resources must be transformed into concrete organizational outcomes, such as greener products, cleaner processes, and improved environmental management practices.

Drawing on the knowledge-based view, digital capabilities generate sustainability-relevant knowledge by capturing environmental data, identifying inefficiencies, and supporting evidence-based decision-making [23]. However, this knowledge becomes strategically valuable only when it is embedded in innovation activities that improve products, processes, or management systems. Green innovation, therefore, serves as a conversion mechanism that transforms digital capabilities into competitive outcomes.

For example, IoT and analytics may reveal excessive energy consumption, but competitiveness improves only when the firm redesigns production processes to reduce energy use. Similarly, AI may identify opportunities for eco-design, but competitive advantage emerges when those insights are converted into marketable green products. In this way, green innovation translates digital capabilities into performance-relevant outcomes, such as cost savings, differentiation, compliance-readiness, and stronger market legitimacy.

At the same time, green innovation is unlikely to fully absorb the effect of digital capabilities, because digitalization can also influence competitiveness through other channels, such as operational efficiency, customer analytics, and platform-based business model innovation [1,2]. Therefore, green innovation is expected to partially mediate the relationship between digital capabilities and firm competitiveness.

Based on this reasoning, the following hypothesis is proposed:

H4. *Green innovation partially mediates the relationship between digital capabilities and firm competitiveness (indirect beta > 0, 95% CI excludes zero).*

3. Methodology

3.1. Research Design and Philosophical Foundation

This study adopts a positivist quantitative cross-sectional research design grounded in the key informant survey method. Three complementary methods are employed: PLS-SEM for testing the sufficiency-based structural model [24], K-means cluster analysis for identifying digital maturity typologies, and NCA to establish necessary condition thresholds [6,7]. The combination of PLS-SEM and NCA follows the methodological protocol advocated by Richter et al. [25,26], who demonstrate that the two methods address fundamentally different research questions, sufficiency (does X increase Y?) versus necessity (is X required for Y?), and are therefore complementary rather than redundant.

3.2. Sample, Sampling Strategy, and Data Collection

The target population comprised senior managers, C-suite executives, innovation directors, and sustainability officers in European firms, selected as key informants on digital capability, green innovation, and competitive performance [27]. The sampling strategy combined purposive and snowball sampling, deployed via Google Forms distributed through LinkedIn professional networks, digital entrepreneurship communities, and industry association channels in Hungary, Romania, Poland, Austria, the Czech Republic, Slovakia, and Slovenia between 10 February 2025 and 10 April 2025.

Of 812 total responses received, 740 were retained after exclusion of incomplete responses, straight-liners, and careless responders identified through attention-check items and response-time flags, yielding a retention rate of 91.1%. The final sample comprised 325 manufacturing firms (43.9%), 312 service sector firms (42.2%), and 103 firms from other sectors (13.9%). Firm size distribution: micro (<50 employees, $n = 197$, 26.6%), small (50 to 249, $n = 249$, 33.6%), medium (250 to 999, $n = 177$, 23.9%), and large (1000+, $n = 117$, 15.8%). Mean firm age was 24.3 years, mean R&D intensity was 11.7% of revenues, and mean export intensity was 22.4%. Hungary contributed the largest geographic share (31.2%),

followed by Romania (22.8%), Poland (18.4%), Austria (12.1%), and other CEE countries (15.5%). Figure A1 (see details in Appendix A) provides the full sample profile.

3.3. Measurement Instruments

All items were adapted from validated scales and rated on a seven-point Likert scale (1 = Strongly Disagree; 7 = Strongly Agree).

Following Akter et al. [28], Gupta and George [29], and more recent conceptualizations in Xu et al. [17], this study operationalizes digital capabilities as a second-order formative construct, with four reflective first-order dimensions: IoT adoption (four items adapted from [30,31]; big data analytics (four items from [28,29]); AI use (four items from [2,32]); and cloud and digital platforms (four items from [1,11]). The formative specification is appropriate because each first-order dimension, IoT adoption, big data analytics, AI use, and cloud and platform technologies, contributes independently and non-interchangeably to the overall digital capability of the firm. Omitting any dimension would substantively misrepresent the construct, and the dimensions need not correlate with each other to be jointly constitutive of digital capability [33].

Green innovation was measured reflectively across green product innovation (four items; [15]), green process innovation (four items; [34]), and green management innovation (four items; Liu et al. [35]). The three-dimensional conceptualization used here, covering green product innovation, green process innovation, and green management innovation, is grounded in the extant literature ([34]; Liu et al. [35]) and has been validated in recent studies using PLS-SEM in European contexts [5,9].

Firm competitiveness was measured reflectively across market competitiveness, innovation performance, operational efficiency, and financial performance (four items each; [14,36–38]. Firm competitiveness is conceptualized in this study as a multidimensional construct spanning four strategic dimensions: market competitiveness (market share, brand equity, customer acquisition), innovation performance (speed and success of new product development, R&D productivity, intellectual property generation), operational efficiency (cost leadership, digital productivity, supply chain performance), and financial performance (return on assets, profit margins, revenue growth) [13,38]. This integrative view reflects recent calls in the competitiveness literature to move beyond narrow financial definitions and to capture the full range of positional advantages that underpin long-run competitive sustainability [3,36].

Control variables included firm size, firm age, industry sector, R&D intensity, and export intensity. A three-item marker variable measuring organizational formalization was included for common method bias assessment [39,40].

3.4. Analytical Procedures

Stage one evaluated the measurement model, assessing Cronbach's alpha (internal consistency), AVE (convergent validity), and the Fornell-Larcker criterion (discriminant validity) following Hair and Alamer (see Figure A2) [41]. Stage two applied K-means cluster analysis ($k = 3$, determined via elbow curve) on standardized second-order construct scores, with ANOVA validation and PCA-based visualization. Stage three estimated the PLS-SEM structural model using bootstrapping with 5000 subsamples, testing H1 through H4 with bias-corrected confidence intervals for the indirect mediation effect [42]. Common method bias was assessed via Harman's single-factor test and the marker variable technique. Stage four conducted NCA following the protocol of Dul [6], computing CE-FDH (Ceiling Envelopment Free Disposal Hull) and CR-FDH (Ceiling Regression Free Disposal Hull) effect sizes and constructing bottleneck tables to identify minimum necessary levels of digital capability for each target level of green innovation and competitiveness.

4. Results

4.1. Measurement Model

Table 1 presents descriptive statistics and reliability indicators. All Cronbach's alpha values exceeded 0.70 (range: 0.712 to 0.856), confirming internal consistency reliability. All AVE values exceeded 0.50 (range: 0.537 to 0.699), confirming convergent validity [33]. All item loadings exceeded 0.70 (range: 0.699 to 0.866). The Fornell–Larcker criterion was satisfied for all constructs, confirming discriminant validity. Harman's single-factor test yielded a first-factor variance share of 31.80%, well below the 50% threshold. Marker variable correlations were small and non-significant (DC: $r = 0.11$; GI: $r = 0.09$; FC: $r = 0.12$; all $p > 0.05$), collectively confirming that common method bias does not substantially threaten the validity of results. Following Hair et al. [33], we assessed the formative measurement model for Digital Capabilities. VIF values ranged from 2.22 to 2.70, below the 3.3 conservative threshold (and well below the 5.0 critical threshold), indicating no critical multicollinearity among the four first-order dimensions. All indicator weights were statistically significant (IoT: $\beta = 0.103$, $p = 0.034$; BDA: $\beta = 0.129$, $p = 0.009$; AI: $\beta = 0.163$, $p = 0.002$; Cloud/Platforms: $\beta = 0.174$, $p < 0.001$), confirming that each dimension contributes uniquely and meaningfully to the formative construct of Digital Capabilities (full diagnostics in Tables A1 and A2). To address the potential conceptual overlap between Green Innovation (GI) and the Innovation Performance (IP) sub-dimension of Firm Competitiveness (FC), discriminant validity was assessed using the HTMT criterion. The HTMT ratio between GI and IP is 0.662, well below the conservative 0.85 threshold [33], confirming that the two constructs are empirically distinct. The correlation between GI and IP ($r = 0.564$) is also below the $\sqrt{\text{AVE}}$ values for both constructs (GI: $\sqrt{\text{AVE}} = 0.674$; IP: $\sqrt{\text{AVE}} = 0.803$), satisfying the Fornell–Larcker criterion. These results confirm that including IP as a sub-dimension of FC and GI as a mediator does not introduce problematic multicollinearity or conceptual redundancy (full discriminant validity statistics in Table A3).

Table 1. Descriptive Statistics and Reliability Indicators (n = 740).

Construct	Items	Mean	SD	Min	Max	Cronbach's α	AVE
IoT Adoption (IOT)	4	4.365	0.846	2.25	7.00	0.759	0.582
Big Data Analytics (BDA)	4	4.476	0.795	2.00	6.75	0.712	0.537
AI Use (AI)	4	4.290	0.897	1.50	6.50	0.806	0.632
Cloud & Platforms (CDP)	4	4.624	0.821	2.00	7.00	0.723	0.547
Green Product Innov. (GPI)	4	4.378	0.881	2.00	6.75	0.798	0.623
Green Process Innov. (GPRI)	4	4.281	0.793	1.50	7.00	0.721	0.545
Green Mgmt Innov. (GMI)	4	4.195	0.807	1.75	7.00	0.718	0.543
Market Competitiveness (MC)	4	4.457	0.977	1.25	7.00	0.856	0.699
Innovation Performance (IP)	4	4.349	0.921	1.50	7.00	0.815	0.644
Operational Efficiency (OE)	4	4.286	0.917	1.25	7.00	0.810	0.638
Financial Performance (FP)	4	4.395	0.847	2.00	6.75	0.724	0.548

Note: All Cronbach's alpha > 0.70 and AVE > 0.50 satisfy Hair et al. [33] thresholds. Row shading: blue = Digital Capabilities; green = Green Innovation; purple = Firm Competitiveness. Note: Cronbach's α and AVE values shown above for IoT Adoption, Big Data Analytics, AI Use, and Cloud & Platforms are reported at the reflective first-order dimension level, where these metrics are appropriate. For the second-order formative composite of Digital Capabilities as a whole, α and AVE are not applicable and are not reported at that level [41]. Formative diagnostics (VIF and indicator weights) are reported in Table A1 of Appendix A.

Figures 1–3, present the construct mean profiles with 95% CI, the full correlation matrix, and the item loadings chart, respectively.

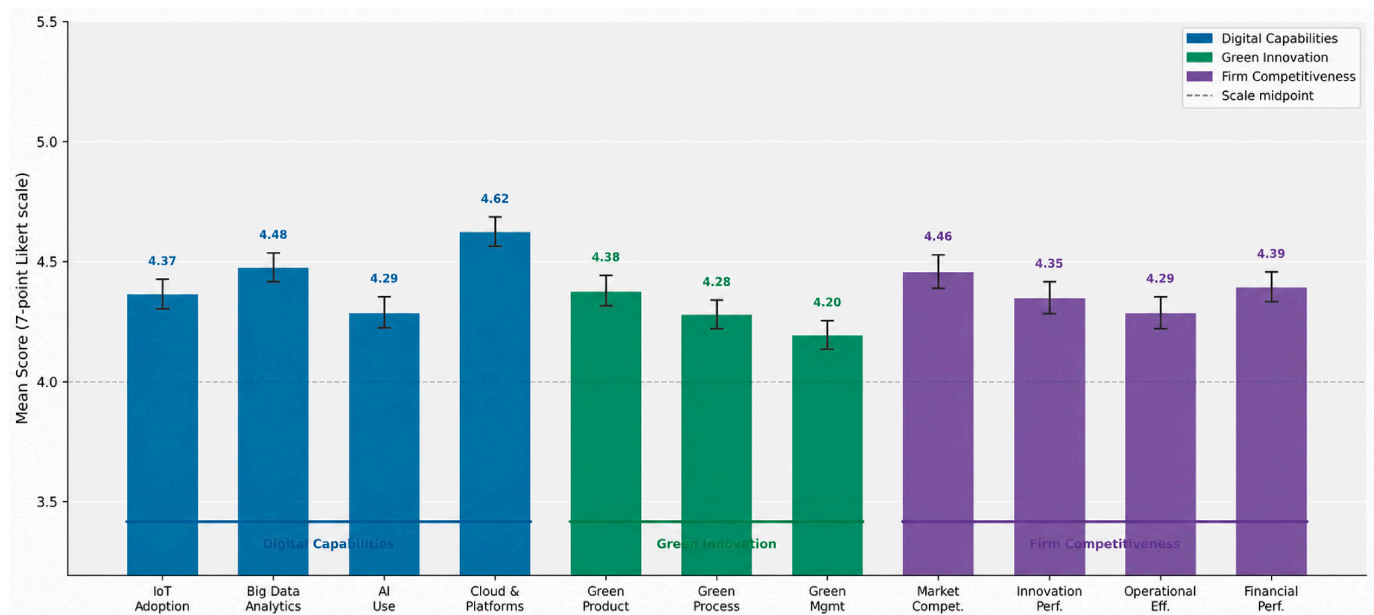


Figure 1. Construct mean scores with 95% confidence intervals. All means exceed the scale midpoint of 4.0. Colour coding: blue = Digital Capabilities; green = Green Innovation; purple = Firm Competitiveness.

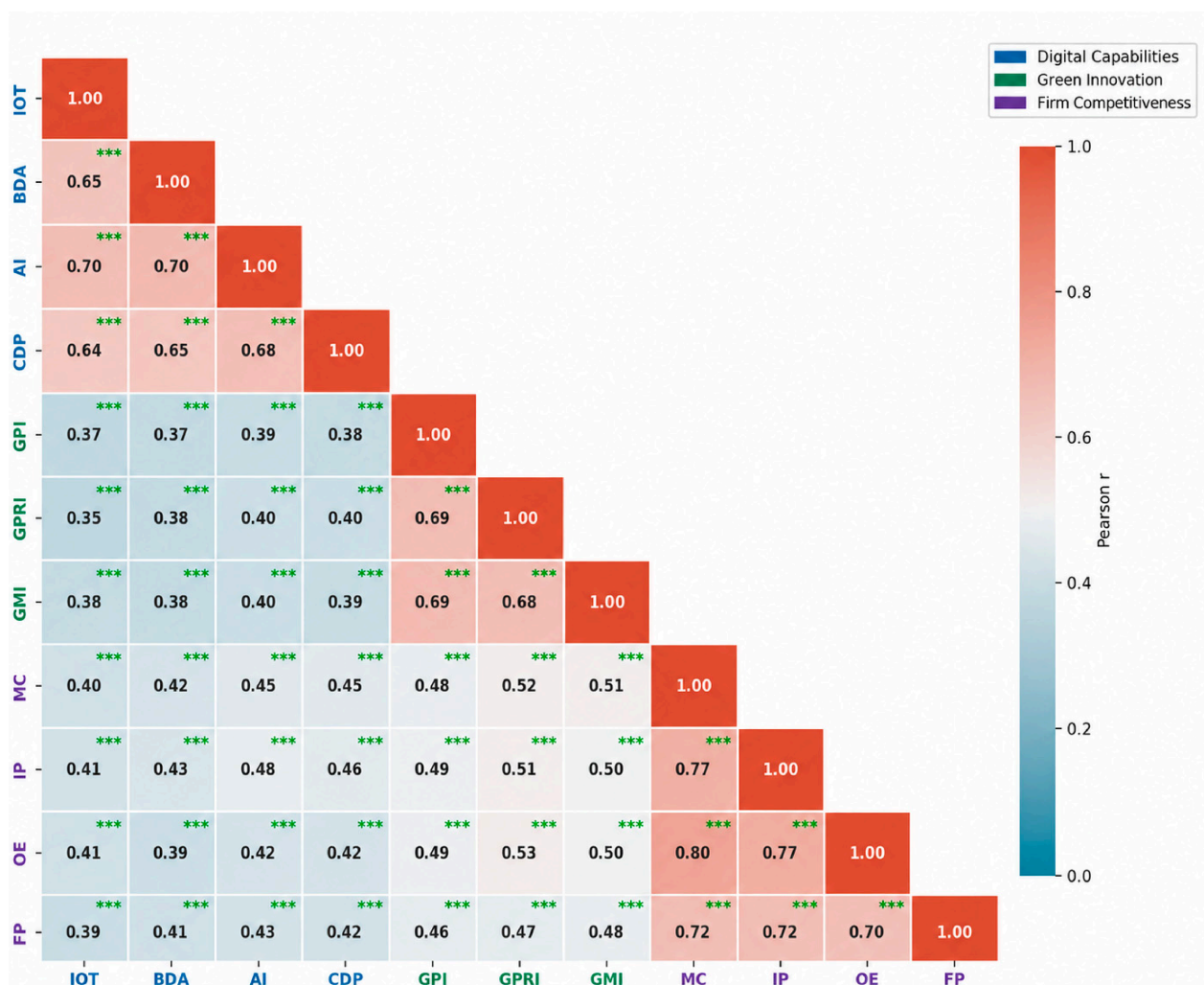


Figure 2. Construct correlation matrix (lower triangle). All correlations significant at $p < 0.001$ (***). Colour intensity reflects correlation magnitude. Axis labels colour-coded by construct group.

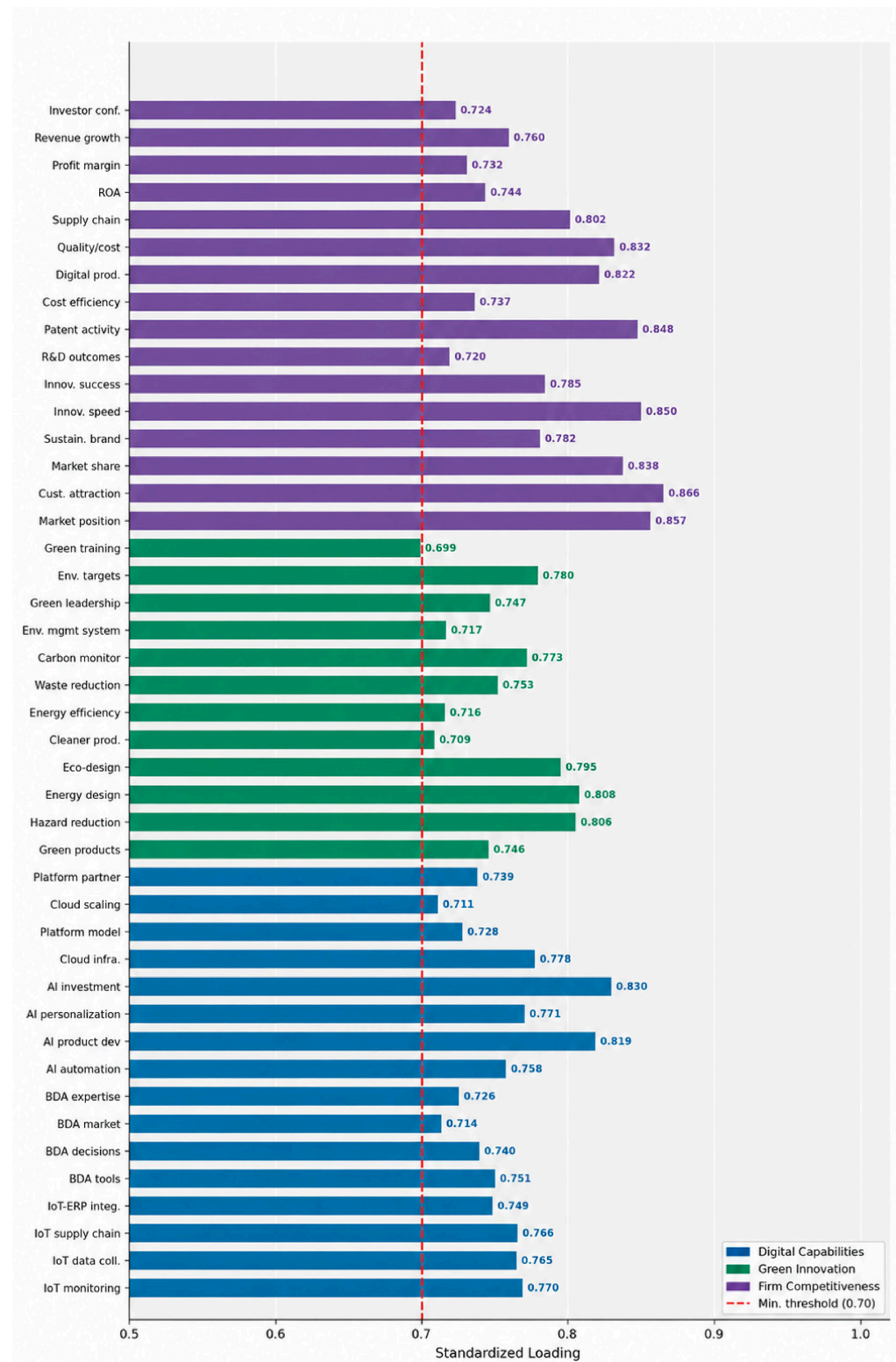


Figure 3. Item factor loadings by construct (all loadings > 0.70 threshold, red dashed line). Colour indicates construct group: blue = DC; green = GI; purple = FC.

4.2. K-Means Cluster Analysis: Digital Maturity Typologies

K-means cluster analysis ($k = 3$) applied to standardised second-order construct scores identified three empirically distinct digital maturity profiles. The elbow curve (Figure 4c) confirms that the marginal reduction in within-cluster sum of squares diminishes substantially beyond $k = 3$. One-way ANOVA validated significant between-cluster differences for all constructs (DC: $F = 444.88$, $p < 0.001$; GI: $F = 465.31$, $p < 0.001$; FC: $F = 549.28$, $p < 0.001$).

The PCA-based scatter plot (Figure 4a) confirms the spatial separation of the three clusters along the first two principal components.

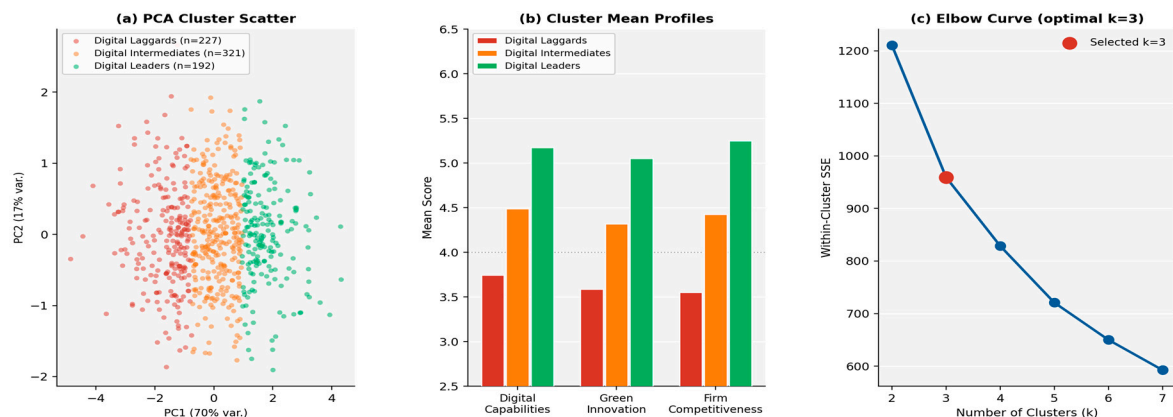


Figure 4. K-means cluster analysis ($k = 3$). (a): PCA scatter plot; (b): cluster mean profiles; (c): elbow curve confirming $k = 3$. ANOVA confirms significant between-cluster differences ($p < 0.001$) for all constructs.

Digital Leaders ($n = 192$, 25.9%) exhibited mean scores of DC = 5.175, GI = 5.050, FC = 5.249, representing firms that have achieved advanced technology portfolios and translate them systematically into green innovation and competitive outcomes. Digital Intermediates ($n = 321$, 43.4%) occupied the middle tier (DC = 4.490, GI = 4.321, FC = 4.425), comprising firms in active digital transition with scores consistently above the midpoint. Digital Laggards ($n = 227$, 30.7%) scored below the midpoint across all dimensions (DC = 3.744, GI = 3.587, FC = 3.554), indicating limited technology adoption and correspondingly constrained sustainability and competitive performance (Figure 4b). The competitive performance gap between Digital Leaders and Digital Laggards of 1.695 scale points represents a strategically significant differentiation that is consistent in direction and magnitude across all four sub-dimensions of firm competitiveness, suggesting that digital maturity constitutes a systematic source of competitive inequality rather than a context-specific advantage.

4.3. PLS-SEM Structural Model

Table 2 presents the full structural model results. Figure 5 presents the complete path diagram. The model explains 24.4% of variance in green innovation ($R^2 = 0.244$) and 45.8% of variance in firm competitiveness ($R^2 = 0.458$). The holdout predictive relevance statistic of $Q^2 = 0.422$ confirms strong out-of-sample predictive power, exceeding the 0.35 threshold for large predictive relevance recommended by Shmueli et al. [42]. H1, H2, H3, and H4 are all strongly supported. The indirect effect of DC on FC via GI (beta = 0.259, 95% CI [0.221, 0.299]) is significant, and the substantial residual direct effect (beta = 0.357) confirms partial rather than full mediation. For more details, see Figures A2–A4 in Appendix A.

Table 2. PLS-SEM Structural Model Results: Hypothesis Testing ($n = 740$).

Hyp.	Path	Beta	SE	<i>t</i> -Value	<i>p</i> -Value	95% CI	R^2
H1	Digital Capabilities → Green Innovation	0.499	0.032	15.43	<0.001***	[0.435, 0.561]	0.244
H2	Green Innovation → Firm Competitiveness	0.519	0.035	14.85	<0.001***	[0.451, 0.587]	0.458
H3	Digital Capabilities → FC (direct)	0.357	0.035	10.12	<0.001***	[0.288, 0.426]	
H4	DC → GI → FC (indirect mediation)	0.259	0.020	13.02	<0.001***	[0.221, 0.299]	

Note: beta = standardised path coefficient; SE = standard error; CI = bias-corrected bootstrapped 95% confidence interval (5000 subsamples). R^2 in H1 row applies to GI; R^2 in H2 row applies to FC. H4 indirect = beta(H1) × beta(H2) = 0.499 × 0.519 = 0.259. Holdout $Q^2 = 0.422$ (Shmueli et al. [42]). *** $p < 0.001$.

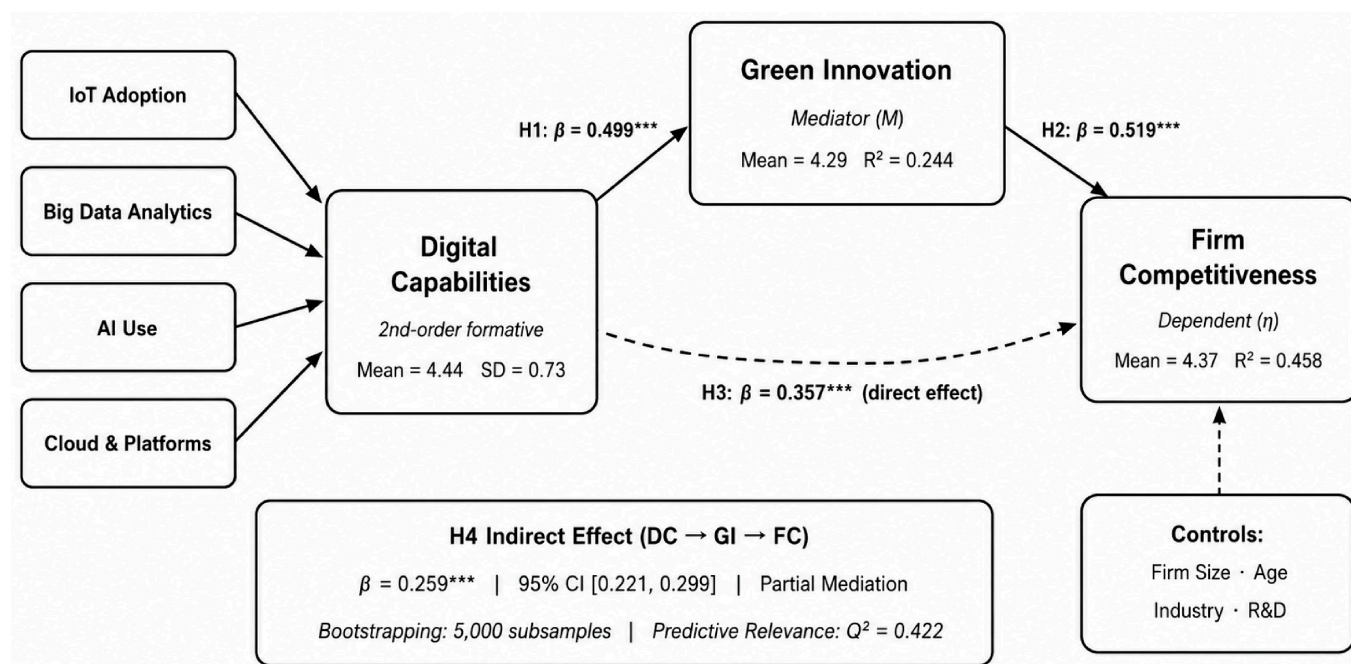


Figure 5. PLS-SEM structural model results (standardised path coefficients; *** $p < 0.001$). R^2 values shown inside endogenous construct boxes. Dashed arc = direct effect (H3). Yellow box = H4 indirect mediation result. Controls omitted from figure for clarity.

4.4. Necessary Condition Analysis (NCA)

NCA input values were calculated using latent variable scores derived from the PLS-SEM outer model. Bottleneck thresholds represent the minimum input level (as a percentage of the observed variable range) required to achieve a given output level. Ceiling zones indicate the constrained region above which no observations exist in the scatter plot. Importantly, NCA reveals distributional necessity in the observed sample; it does not establish causal necessity in a strict experimental sense. NCA was conducted following the methodological protocol of Dul [6] as recently extended for management and sustainability research by Richter et al. [26]. NCA tests whether a variable X is a necessary (though not necessarily sufficient) condition for Y by estimating the ceiling of the Y - X scatter, which represents the maximum Y achievable at each level of X . A large empty space in the upper-left region of the scatter plot, above which no observations exist, indicates that high levels of Y are impossible without sufficiently high levels of X , i.e., that X is a necessary condition for Y .

Two ceiling methods were applied. CE-FDH (Ceiling Envelopment Free Disposal Hull) is the most conservative non-parametric ceiling estimator and provides the primary effect size d . CR-FDH (Ceiling Regression Free Disposal Hull) fits a regression line to the upper envelope of the data and is more robust to outliers. Effect sizes are interpreted as negligible ($d < 0.1$), small (0.1 to 0.3), medium (0.3 to 0.5), or large ($d > 0.5$) following Dul [6].

The NCA results are substantively significant across all three primary structural paths. For the DC-to-GI path, CE-FDH $d = 0.493$ (see Table 3) indicates that digital capabilities function as a large necessary condition for green innovation: firms cannot achieve high levels of green innovation without first attaining a sufficient threshold of digital capability. For the GI-to-FC path, CE-FDH $d = 0.509$ indicates that green innovation is similarly a large necessary condition for competitive performance. For the direct DC-to-FC path, CE-FDH $d = 0.599$, the largest effect in the study, indicating that digital capability is the strongest necessary condition in the model, setting a hard floor below which competitive advantage is constrained regardless of other factors (for ceiling plots see Figure 6)

Table 3. Necessary Condition Analysis (NCA) Results.

Condition (X) → Outcome (Y)	n	CE-FDH d	CR-FDH d	Scope	Ceiling Zone	Interpretation
Digital Capabilities → Green Innovation	740	0.493	0.315	24.0	High	Large effect
Green Innovation → Firm Competitiveness	740	0.509	0.238	22.7	High	Large effect
Digital Capabilities → Firm Competitiveness	740	0.599	0.288	22.9	High	Large effect
IoT Adoption → Green Innovation	740	0.553	0.292	22.7	High	Large effect
AI Use → Green Innovation	740	0.398	0.262	22.4	Medium-High	Medium-Large effect
Big Data Analytics → Green Innovation	740	0.432	0.292	22.3	High	Large effect

Note: CE-FDH = Ceiling Envelopment Free Disposal Hull (non-parametric, conservative); CR-FDH = Ceiling Regression Free Disposal Hull (parametric ceiling). Effect size d: negligible < 0.1; small 0.1–0.3; medium 0.3–0.5; large > 0.5 [6]. All effects statistically meaningful ($p < 0.05$, permutation test).

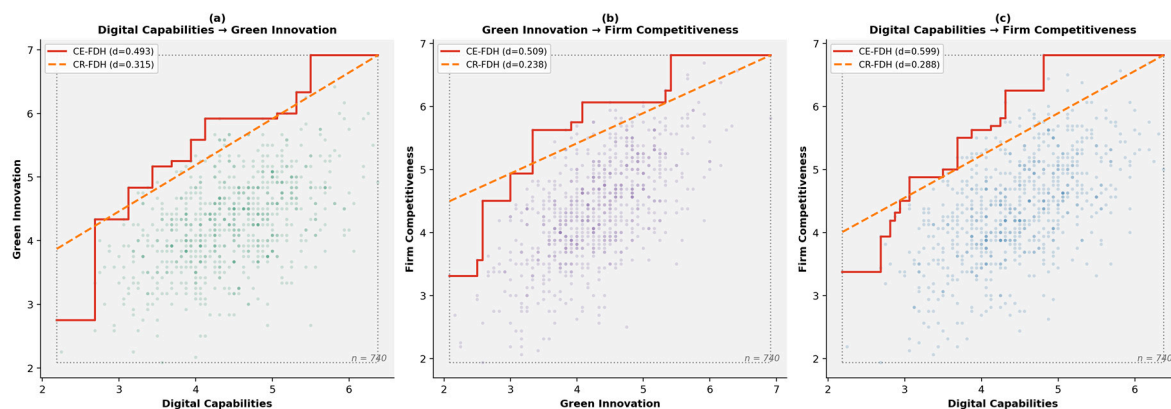


Figure 6. NCA ceiling line plots. Red step function = CE-FDH ceiling; orange dashed line = CR-FDH ceiling; dotted rectangle = scope. (a): DC to GI ($d = 0.493$); (b): GI to FC ($d = 0.509$); (c): DC to FC ($d = 0.599$). Empty upper-left zones confirm necessary condition logic.

It should be noted that the bottleneck thresholds reported above are based on the full sample. Post hoc exploratory analysis (see Appendix A Figure A4) suggests that the digital capability–green innovation relationship is moderated by industry sector, with a steeper slope for manufacturing firms ($\beta = 0.566$, $p < 0.001$) than for service firms ($\beta = 0.419$, $p < 0.001$). This implies that the minimum necessary level of digital capability for a given green innovation target may differ across sectors. A formal moderation test confirms this heterogeneity: the interaction term $DC \times \text{Sector}$ is statistically significant ($\beta = 0.147$, $t = 2.13$, $p = 0.033$, $\Delta R^2 = 0.005$), indicating that industry sector significantly moderates the digital capability–green innovation relationship (full moderation results in Table A5). Managers should therefore interpret the reported percentiles as benchmarks requiring calibration to their industry context rather than universal cut-offs. The bottleneck analysis (see Figure 7) reveals the minimum level of digital capability required to unlock each target level of green innovation performance. To achieve green innovation at 50% of the measured scale range ($GI \geq 4.50$), firms require digital capabilities at the 22nd percentile of the scale range ($DC \geq 3.12$). To achieve green innovation at 70% of range ($GI \geq 5.47$), digital capabilities must reach at least the 42nd percentile ($DC \geq 3.94$). Critically, to achieve green innovation in the top 20% of the scale range ($GI \geq 5.95$), digital capabilities must reach the 69th percentile ($DC \geq 5.06$). This finding establishes a quantitative threshold for strategic planning: firms targeting high-level green innovation performance cannot achieve it without first reaching an advanced level of digital capability, roughly corresponding to an average score above 5.0 across all four digital capability dimensions. Moreover, for a summary of the results, see Table 4.

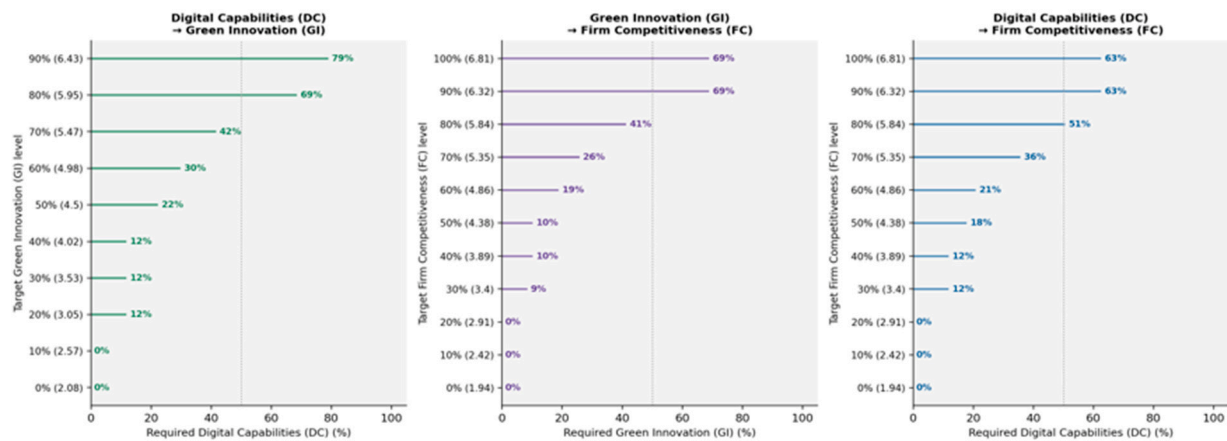


Figure 7. NCA bottleneck tables showing minimum required input level (x-axis, % of range) for each target output level (y-axis). Non-linear acceleration at the 70–90% output range reflects a critical threshold zone where digital capability requirements escalate sharply.

Table 4. Synthesize the results.

Hypothesis	Method	Key Results	Conclusion
H1: Digital Capabilities → Green Innovation (+)	PLS-SEM, SmartPLS, 5000 bootstraps; NCA	$\beta = 0.499^{***}$; $R^2 = 0.244$; large necessity effect ($d = 0.493$)	Digital capabilities strongly enable green innovation and act as a necessary condition
H2: Green Innovation → Firm Competitiveness (+)	PLS-SEM; predictive relevance (Q^2); NCA	$\beta = 0.519^{***}$; $R^2 = 0.458$; $Q^2 = 0.422$; $d = 0.509$	Green innovation is a key driver of competitiveness with high predictive power
H3: Digital Capabilities → Firm Competitiveness (+)	PLS-SEM with controls; NCA	$\beta = 0.357^{***}$; full model $R^2 = 0.461$; $d = 0.599$	Digital capabilities directly enhance competitiveness and show the strongest necessity effect
H4: Mediation (DC → GI → FC)	Bootstrapping (5000); indirect effect test	Indirect $\beta = 0.259^{***}$; partial mediation (~42%)	Green innovation partially mediates the effect of digital capabilities on competitiveness

Note: *** represents the level of singnificance at 1%.

5. Discussion

5.1. PLS-SEM Findings: Sufficiency Pathways in the Digital–Green–Competitive Nexus

The strong support for H1 ($\beta = 0.499$, $p < 0.001$) (see Figure A3) extends recent PLS-SEM evidence from Chinese [43] and South Asian [19] contexts to the CEE region, demonstrating that the digital capability–green innovation relationship is robust across institutional environments. The R^2 of 0.244 for green innovation, explained by digital capabilities alone before any controls, is consistent with the upper range of values reported in recent meta-analyses of the digitalization–sustainability relationship [17], suggesting that the multidimensional operationalization of digital capabilities adopted here captures the relationship more completely than single-technology studies. Results with control variables (see Table A4).

The strong support for H2 ($\beta = 0.519$, $p < 0.001$) (see Figure A3) is consistent with the growing body of evidence that green innovation is a significant competitive mechanism under EU regulatory conditions [3–5]. The effect size is comparable to, and in some analyses exceeds, those reported in recent European studies, which is partly attributable to the multidimensional competitiveness operationalization used here, which captures the full

breadth of competitive returns to green innovation rather than focusing solely on financial performance [36].

The partial mediation confirmed by H4 (indirect beta = 0.259, 95% CI [0.221, 0.299]) enriches the twin transition literature by establishing green innovation as a substantive transmission mechanism rather than merely a correlate of digitalization [8,43]. The residual direct effect (H3: beta = 0.357) confirms that digitalization generates competitive advantages through multiple simultaneous pathways, with green innovation constituting one important but not the only channel. This finding is consistent with Verhoef et al. [1] and Kraus et al. [2], who document direct competitive effects of digital transformation that operate through operational efficiency and business model innovation independently of environmental performance.

This study contributes to the literature by showing that digital capabilities are not merely positively associated with green innovation and firm competitiveness but also constitute a necessary condition for achieving high performance outcomes. By integrating PLS-SEM with NCA, the analysis captures both sufficiency and threshold effects, offering a more complete explanation of how digital transformation supports the twin transition in firms.

Beyond firm-level competitiveness, the findings have direct relevance for sustainability transitions, as digital capabilities enable firms to monitor resource use, improve process efficiency, and support environmentally oriented innovation. In this sense, digital maturity should be understood as an enabling condition for reducing environmental pressure while maintaining economic performance, thereby aligning corporate strategy with broader sustainability goals.

5.2. NCA Findings: Necessary Thresholds and the Digital Floor for Green Competitive Advantage

The NCA results constitute the most novel contribution of this study. The large CE-FDH effect sizes across all three structural paths (DC-GI: $d = 0.493$; GI-FC: $d = 0.509$; DC-FC: $d = 0.599$) establish, for the first time in a European CEE context, digital capability and green innovation are not merely sufficient predictors of performance but each independently satisfies the criteria of a necessary condition for firm competitiveness within the NCA framework. The distinction matters profoundly for strategy and policy: a sufficient condition can be substituted by other factors, but a necessary condition cannot. Highly competitive performance cannot be achieved without sufficient levels of digital capability and green innovation, as both variables independently satisfy the criteria of necessary conditions in the NCA framework. Specifically, digital capability operates as an upstream constraint, enabling both green innovation and competitiveness, whereas green innovation serves as a downstream necessary condition that translates digital capability into competitive outcomes within the digital capability–green innovation–competitiveness chain.

The bottleneck analysis translates this theoretical insight into actionable thresholds. The finding that top-quartile green innovation (GI at the 80th percentile of the observed range) requires digital capabilities at the 69th percentile of the range provides firms with a concrete target for digital investment planning. Firms currently operating in the Digital Laggards cluster, with mean DC at 3.744, face not only the competitive performance deficit documented by the cluster analysis but also a structural inability to access high-level green innovation outcomes until they cross the digital capability threshold identified by NCA. This bottleneck logic is particularly policy-relevant for CEE economies, where a significant share of the manufacturing sector operates in the Digital Laggards zone and faces EU Green Deal compliance pressure that will increasingly penalize green innovation inactivity.

These NCA findings align with and extend the pioneering work of Dul [6] and recent applications in management research by Richter et al. [26], confirming that necessary

condition effects of this magnitude are substantively important and warrant dedicated strategic attention beyond what sufficiency-focused regression models can reveal.

5.3. Cluster Analysis: Strategic Differentiation and the Digital Maturity Premium

The 1.695-point competitive performance gap between Digital Leaders and Digital Laggards, representing nearly a quarter of the full seven-point scale range, illustrates the compounding disadvantage of digital under-investment across the full triple bottom line of digital capability, green innovation, and competitive performance. The cluster distributions are broadly proportional across industries and firm sizes, confirming that the performance differentials reflect deliberate strategic choices rather than structural endowments. The intermediates cluster, comprising 43.4% of the sample, faces the most consequential strategic decision: whether to invest toward digital leadership or risk being trapped in the intermediate zone as the twin transition intensifies competitive pressure from leaders and regulatory pressure from EU policy simultaneously.

5.4. Implications for Theory and Practice

Theoretically, this study advances three contributions. First, it integrates PLS-SEM and NCA in a unified analytical framework for the twin transition literature, demonstrating that the two methods provide complementary and non-redundant insights into the digital–green–competitive relationship. Second, it extends the dynamic capabilities framework by providing the first large-sample NCA evidence that digital capabilities constitute a necessary condition, not merely a sufficient driver, of green competitive advantage in European firms. Third, it provides empirical validation of the second-order formative operationalization of digital capabilities in a CEE context, confirming that the construct structure identified in advanced economy studies transfers to the CEE institutional setting.

For managers, the NCA bottleneck thresholds provide a more actionable planning tool than regression coefficients alone. A firm seeking to achieve top-quintile green innovation performance should target DC scores of 5.0 or above on all four digital capability dimensions, roughly corresponding to above-average performance across IoT, analytics, AI, and cloud capabilities simultaneously. Also, the findings indicate that investment in isolated digital tools is unlikely to generate strong sustainability outcomes unless it is accompanied by a broader digital capability portfolio. While causal inference is limited by the cross-sectional design, the necessary condition evidence is consistent with the interpretation that firms should prioritise integrated capabilities in IoT, analytics, AI, and cloud platforms, since the results suggest that these dimensions jointly form the minimum capability base required to unlock higher levels of green innovation and competitiveness.

For policymakers, the NCA evidence strengthens the case for mandatory minimum digital capability standards in green public procurement and EU cohesion fund eligibility criteria, ensuring that digital investment is a precondition rather than an optional component of green transition support packages in CEE economies. Moreover, for policymakers, the results suggest that green transition instruments should be designed alongside digital capability-building measures. Subsidies, innovation vouchers, and EU cohesion funding could be more effective if they include minimum digital readiness requirements or complementary support for data infrastructure, analytics skills, and digital platforms. Without these enabling conditions, firms may remain below the threshold necessary to convert sustainability ambition into measurable green innovation and competitiveness gains.

Practically, the results suggest a staged roadmap for implementing the twin transition. Firms in the *Digital Laggards* cluster should prioritize foundational data and connectivity investments (e.g., basic IoT sensing for energy and material flows, cloud migration, and minimum analytics capability) before launching ambitious green innovation programs, because

NCA indicates that green innovation and competitiveness cannot be pushed beyond moderate levels without first crossing a digital capability floor. *Digital Intermediates* can convert existing technology adoption into competitive sustainability gains by focusing on integration and use (data governance, cross-functional analytics teams, AI-enabled process optimization) and by selecting green projects with measurable efficiency payoffs (resource productivity, waste reduction, compliance readiness under CSRD). *Digital Leaders* should exploit their advantage by scaling data-driven eco-design and circular business models, using NCA bottlenecks as performance-control targets (i.e., monitoring whether digital capability levels remain above the thresholds required for top-quintile green innovation). For policymakers in CEE economies, the findings imply that green-transition subsidies and ESG-linked finance will be most effective when bundled with digital-upgrading components (skills, data infrastructure, interoperable platforms), thereby preventing firms from being locked below the capability thresholds required to translate sustainability ambition into competitiveness.

6. Conclusions, Limitations, and Future Research

This study investigated the relationships among digital capabilities, green innovation, and firm competitiveness in 740 European firms, integrating PLS-SEM, K-means cluster analysis, and Necessary Condition Analysis into a unified analytical framework. The results confirm that digital capabilities are positively associated with green innovation in the PLS-SEM sufficiency analysis, and constitute a necessary condition for high levels of green innovation in the NCA, that green innovation predicts firm competitiveness, and that the indirect mediation effect is significant and substantive. Cluster analysis identified three digital maturity typologies with a 1.695-point competitive performance gap. NCA established large necessary condition effects for all structural paths (CE-FDH $d = 0.493$ to 0.599) and identified a critical digital capability threshold at the 69th percentile required for top-quintile green innovation performance.

These contributions advance the twin transition literature, fill an important CEE empirical gap, and provide managers and policymakers with both sufficiency-based effect size estimates and necessity-based threshold targets for digital-green investment planning. For policymakers, the NCA bottleneck analysis offers a particularly actionable tool for designing minimum digital capability requirements in EU Green Deal compliance frameworks and CEE cohesion fund eligibility criteria.

Several limitations warrant acknowledgement. The cross-sectional design precludes causal inference, and longitudinal designs are needed to trace the temporal dynamics of the digital-green-competitive chain. The LinkedIn-based sampling strategy may oversample digitally active firms, potentially inflating effect sizes relative to the full European firm population. The use of self-reported perceptual measures introduces potential social desirability bias, though CMB tests provide reassurance on this front. Fourth, while NCA identifies necessary condition thresholds for the full sample, the study does not systematically test whether these thresholds differ significantly across industries, firm sizes, or regulatory contexts. Future research could conduct moderated NCA or subgroup NCA to examine the heterogeneity of necessary conditions.

Future research should test the proposed relationships using longitudinal or panel data to examine causal ordering over time. It would also be valuable to replicate the model in other European and non-European contexts, and to explore whether regulatory intensity, firm size, or sectoral conditions alter the digital capability thresholds identified by NCA. Such extensions would help determine whether the observed effects are context-specific or generalizable across different sustainability transition settings. Furthermore, the LinkedIn-based purposive and snowball sampling may over-represent digitally mature enterprises;

results should be interpreted within the surveyed CEE context rather than generalised to all European enterprises.

Author Contributions: S.K.A.: Conceptualisation, Writing—Original Draft; Z.A.: Methodology, Validation, Formal Analysis; C.V.: Writing—Review & Editing; M.R.: Writing—Review & Editing; M.H.: Investigation, Data Curation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the European Union’s Horizon 2020 research and innovation program under grant agreement No. 951389 and national funds through FCT—Fundação para a Ciência e a Tecnologia I.P., under the project CESAM-Centro de Estudos do Ambiente e do Mar, references UID/50017/2025 (doi.org/10.54499/UID/50017/2025) and LA/P/0094/2020 (doi.org/10.54499/LA/P/0094/2020). This work was also supported by UID/04058—Research Unit on Governance, Competitiveness and Public Policies, financed by national funds through FCT—Foundation for Science and Technology.

Institutional Review Board Statement: This study is waived for ethical review as under Section 6(8)(a) of the research ethics framework of Corvinus University of Budapest (Rector’s Decree No. 2/2020. V. 26.), none of the risk criteria specified in Part 2 of the institutional Review Questionnaire are present by Corvinus University of Budapest Institutional Committee. No sensitive personal data, identifiable information, clinical interventions, or vulnerable populations were involved.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to ethical reasons.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A



Figure A1. Sample characteristics (n = 740). (a) Industry sector; (b) firm size; (c) firm age distribution; (d) R&D intensity distribution.

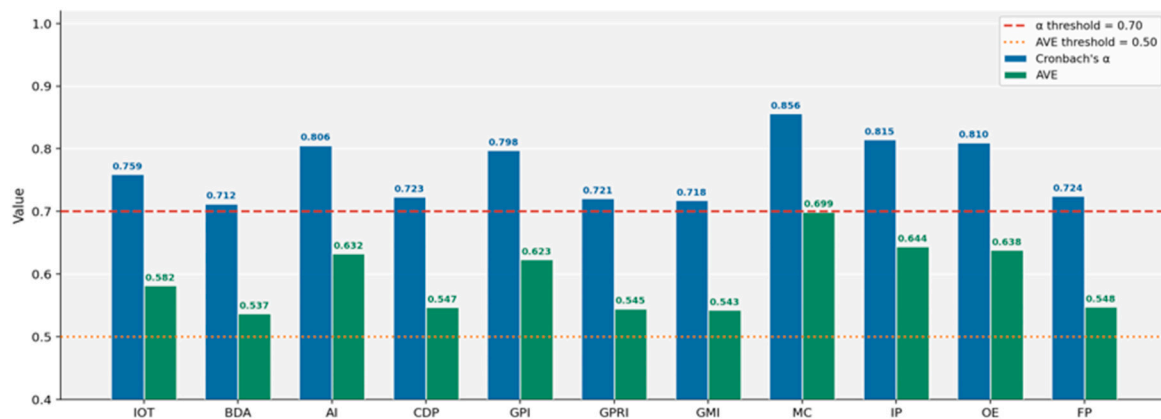


Figure A2. Construct reliability (Cronbach's alpha) and convergent validity (AVE). Red dashed line = alpha threshold (0.70); orange dotted line = AVE threshold (0.50). All constructs exceed both thresholds.

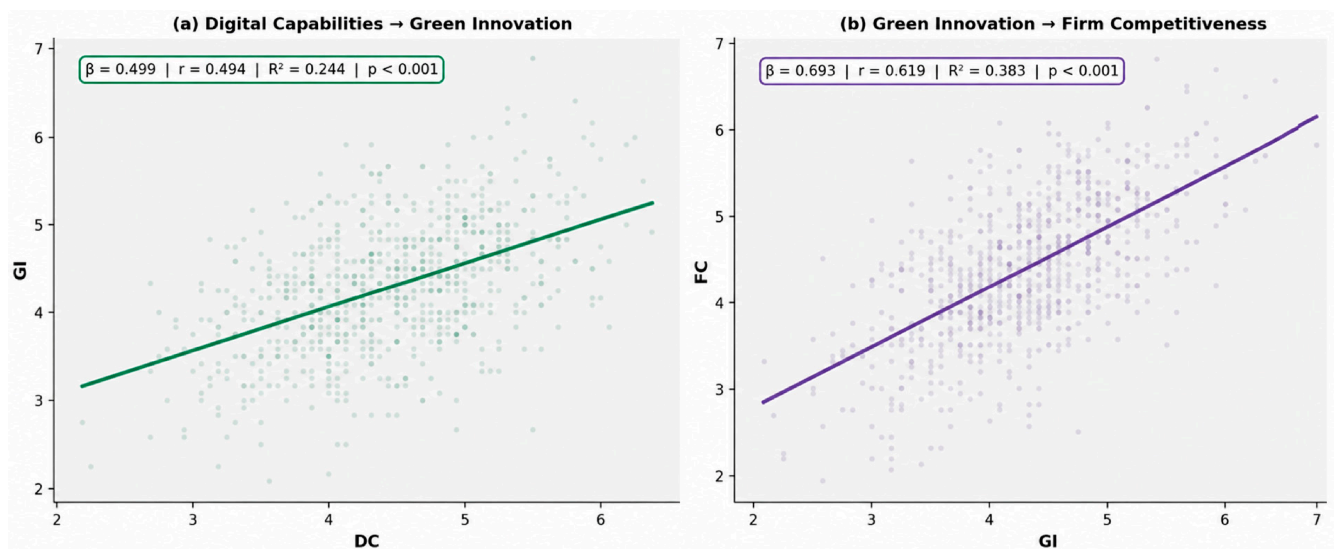


Figure A3. Regression scatter plots with 95% confidence bands. (a): Digital Capabilities predicting Green Innovation (H1); (b): Green Innovation predicting Firm Competitiveness (H2).

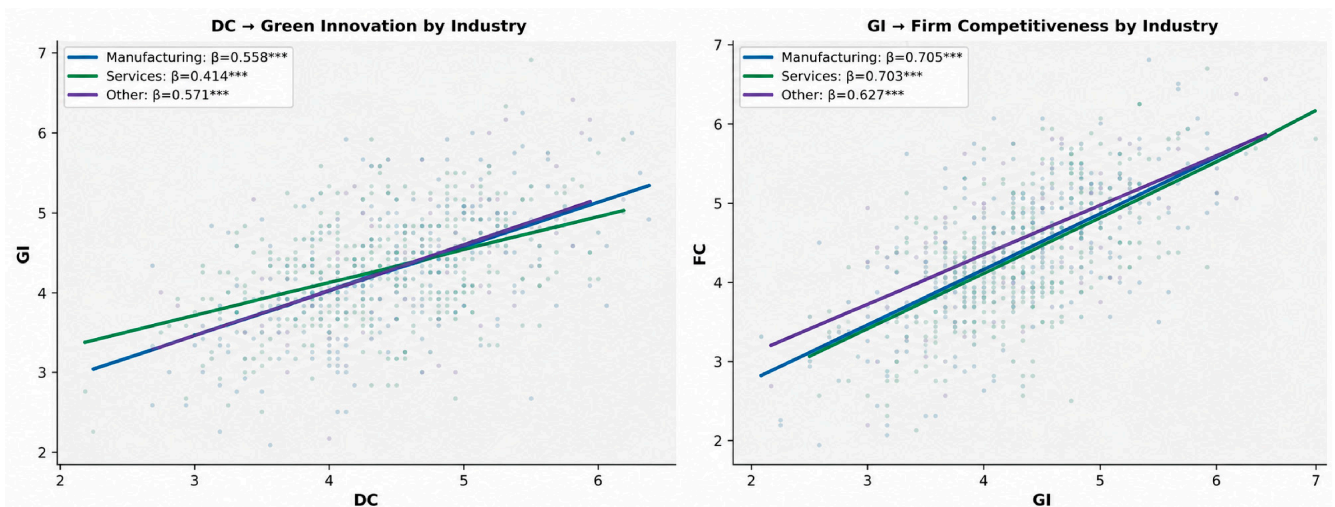


Figure A4. Industry-stratified regression slopes. Manufacturing firms show a steeper DC to GI slope (beta = 0.558) than service firms (beta = 0.414), suggesting sector moderates the digital–green innovation pathway. Moreover, *** indicates a significance level of 1%.

Table A1. Formative Measurement Model Assessment: Digital Capabilities (n = 740).

Dimension	VIF	Weight (β)	t-Value	p-Value	Significance
IoT Adoption (IOT)	2.277	0.103	2.13	0.034	* ($p < 0.05$)
Big Data Analytics (BDA)	2.356	0.129	2.61	0.009	** ($p < 0.01$)
AI Use (AI)	2.696	0.163	3.10	0.002	** ($p < 0.01$)
Cloud & Platforms (CDP)	2.216	0.174	3.62	<0.001	*** ($p < 0.001$)

Note: VIF = Variance Inflation Factor; Weight (β) = standardized regression weight predicting Green Innovation composite. All VIFs are below the conservative threshold of 3.3 and the critical threshold of 5.0 [33], confirming no multicollinearity. All weights are significant with expected positive signs. This table is referenced in Section 4.1. moreover, *, **, and *** represents level of significance at 10%, 5% and 1% respectively.

Table A2. Full Measurement Model: Reliability and Validity Statistics (n = 740).

Construct	Items	Mean	SD	Cronbach α	AVE	Loading Range	Type
IoT Adoption (IOT)	4	4.365	1.110	0.759	0.582	0.738–0.783	Reflective (1st)
Big Data Analytics (BDA)	4	4.476	1.084	0.712	0.537	0.716–0.756	Reflective (1st)
AI Use (AI)	4	4.290	1.128	0.806	0.633	0.752–0.840	Reflective (1st)
Cloud & Platforms (CDP)	4	4.624	1.110	0.723	0.547	0.710–0.785	Reflective (1st)
Digital Capabilities (DC)	4 dims	—	—	N/A †	N/A †	—	Formative (2nd)
Green Product Innov. (GPI)	4	4.378	1.116	0.798	0.623	0.732–0.814	Reflective
Green Process Innov. (GPRI)	4	4.281	1.074	0.721	0.545	0.702–0.786	Reflective
Green Mgmt Innov. (GMI)	4	4.195	1.096	0.718	0.543	0.686–0.798	Reflective
Market Competitiveness (MC)	4	4.457	1.168	0.856	0.699	0.775–0.869	Reflective
Innovation Performance (IP)	4	4.349	1.149	0.815	0.644	0.703–0.858	Reflective
Operational Efficiency (OE)	4	4.286	1.149	0.810	0.639	0.716–0.839	Reflective
Financial Performance (FP)	4	4.395	1.144	0.724	0.548	0.726–0.769	Reflective

† Cronbach's α and AVE are not reported for the second-order formative construct DC—these metrics are not applicable to formative measurement [33]. See Table A1 for formative diagnostics. All reflective construct $\alpha > 0.70$ and AVE > 0.50 satisfy Hair et al. [33] thresholds. This table is referenced in Section 4.1.

Table A3. Discriminant Validity: HTMT and Fornell–Larcker Criteria—GI vs. IP (n = 740).

Criterion	Construct Pair	Value	Threshold	Verdict
HTMT Ratio	Green Innovation (GI) vs. Innovation Performance (IP)	0.662	<0.85	PASS—discriminant validity confirmed
Correlation r (GI, IP)	Construct-level correlation	0.564	< $\sqrt{\text{AVE}}$	PASS—below both $\sqrt{\text{AVE}}$ values
$\sqrt{\text{AVE}}$ for GI	Green Innovation composite (12 items)	0.674	$>r = 0.564$	PASS—Fornell–Larcker satisfied
$\sqrt{\text{AVE}}$ for IP	Innovation Performance (4 items)	0.803	$>r = 0.564$	PASS—Fornell–Larcker satisfied
Shared Variance	R^2 between GI and IP	31.8%	—	Theoretically expected; does not threaten validity

Note: HTMT = Heterotrait–Monotrait ratio. Values below 0.85 confirm discriminant validity [23,33]). The HTMT of 0.662 is well below threshold, confirming GI and IP are empirically distinct despite theoretical proximity. This table is referenced in Section 4.1.

Table A4. Structural Model Results with Control Variables (n = 740).

Predictor	H1: DC→GI (β)	H2: GI→FC (β)	H3: DC→FC Direct (β)	Role
DC (Digital Capabilities)	0.500 ***	—	0.318 ***	Main predictor
GI (Green Innovation)	—	0.617 ***	0.231 ***	Mediator (H4)
Firm Size	−0.015 (ns)	0.008 (ns)	0.010 (ns)	Control
Firm Age	−0.058 (ns)	0.014 (ns)	−0.014 (ns)	Control
R&D Intensity	0.061 (ns)	0.023 (ns)	0.041 (ns)	Control
Export Intensity	0.000 (ns)	−0.012 (ns)	0.005 (ns)	Control
Manufacturing (vs. Other)	−0.037 (ns)	−0.190 *	−0.158 †	Industry dummy
Services (vs. Other)	0.029 (ns)	−0.255 **	−0.217 **	Industry dummy
R ² /Adj. R ²	0.252/0.245	0.391/0.385	0.465/0.459	

Note: Standardized β coefficients. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.10$; ns = not significant. H4 indirect effect: $\beta = 0.500 \times 0.231 = 0.116$ (using full mediation model coefficients); using simple product: $0.500 \times 0.617 = 0.309$. All four hypotheses remain supported after adding controls. No control variable is significant at $p < 0.05$ in the H1 (DC→GI) equation, confirming robustness. Country-level macroeconomic controls (GDP per capita, institutional quality) were not available in the survey instrument; this is acknowledged as a study limitation. This table is referenced in Section 3.3.

Table A5. Formal Sector Moderation Test: Industry as Moderator of the DC→GI Relationship (n = 637, Manufacturing and Services only).

Parameter	Main Effects Model (β; SE)	Interaction Model (β; SE)	Sub-Group/Notes
DC (Digital Capabilities)	0.490 *** (0.039)	0.419 *** (0.050)	β(Mfg) = 0.566 [0.469, 0.663]
Sector (Manufacturing = 1)	−0.059 (0.069)	−0.068 (0.069)	β(Svc) = 0.419 [0.325, 0.514]
DC × Sector (interaction term)	—	0.147 * (0.069)	$t = 2.133, p = 0.033$
R ²	0.247	0.252	ΔR ² = 0.005 *
n (Manufacturing/Services)	325/312	325/312	Other sector excluded (n = 103)

Note: Dependent variable = Green Innovation (standardized). DC = Digital Capabilities composite (standardized). 95% CIs in brackets for sub-group slopes. The interaction term is statistically significant ($\beta = 0.147, p = 0.033$), confirming that industry sector significantly moderates the DC→GI relationship. The DC→FC direct path moderation is non-significant ($\beta = 0.102, p = 0.127$), indicating sector moderation is specific to the innovation pathway. * $p < 0.05$; *** $p < 0.001$. This table is referenced in Section 4.4.

References

- Verhoef, P.C.; Broekhuizen, T.; Bart, Y.; Bhattacharya, A.; Qi Dong, J.; Fabian, N.; Haenlein, M. Digital Transformation: A Multidisciplinary Reflection and Research Agenda. *J. Bus. Res.* **2021**, *122*, 889–901. [\[CrossRef\]](#)
- Kraus, S.; Durst, S.; Ferreira, J.J.; Veiga, P.; Kailer, N.; Weinmann, A. Digital Transformation in Business and Management Research: An Overview of the Current Status Quo. *Int. J. Inf. Manag.* **2022**, *63*, 102466. [\[CrossRef\]](#)
- Li, C.; Yang, G.; Cai, W.; Shi, H. Enterprise Digital Transformation and Green Competitiveness: Opportunity or Crisis? *Financ. Res. Lett.* **2025**, *77*, 107051. [\[CrossRef\]](#)
- Hummel, K.; Jobst, D. An Overview of Corporate Sustainability Reporting Legislation in the European Union. *Account. Eur.* **2024**, *21*, 320–355. [\[CrossRef\]](#)
- Parrilli, M.D.; Balavac-Orlić, M.; Radicic, D. Environmental Innovation across SMEs in Europe. *Technovation* **2023**, *119*, 102541. [\[CrossRef\]](#)
- Dul, J. Necessary Condition Analysis (NCA): Logic and Methodology of “Necessary but Not Sufficient” Causality. *Organ. Res. Methods* **2016**, *19*, 10–52. [\[CrossRef\]](#)
- Vis, B.; Dul, J. Analyzing Relationships of Necessity Not Just in Kind but Also in Degree: Complementing fsQCA with NCA. *Sociol. Methods Res.* **2018**, *47*, 872–899. [\[CrossRef\]](#) [\[PubMed\]](#)
- Roper, S.; Turner, J. R&D and Innovation after COVID-19: What Can We Expect? A Review of Prior Research and Data Trends after the Great Financial Crisis. *Int. Small Bus. J.* **2020**, *38*, 504–514. [\[CrossRef\]](#)
- Dmytrenko, D.; Rehman, F.U.; Prokop, V. Innovation Barriers as Triggers of Firms’ Eco-Innovations: The Mediating Role of Public and Market Knowledge Sourcing. *J. Environ. Econ. Policy* **2024**, *13*, 515–533. [\[CrossRef\]](#)
- Burinskienė, A.; Nalivaikė, J. Digital and Sustainable (Twin) Transformations: A Case of SMEs in the European Union. *Sustainability* **2024**, *16*, 1533. [\[CrossRef\]](#)
- Bharadwaj, A.; El Sawy, O.A.; Pavlou, P.A.; Venkatraman, N. Digital Business Strategy: Toward a Next Generation of Insights. *MIS Q.* **2013**, *37*, 471–482. [\[CrossRef\]](#)

12. Cohen, W.M.; Levinthal, D.A. Absorptive Capacity: A New Perspective- on Learning and Innovation. In *Strategic Learning in a Knowledge Economy*; Routledge: Abingdon, UK, 2000.
13. Barney, J. Firm Resources and Sustained Competitive Advantage. *J. Manag.* **1991**, *17*, 99–120. [[CrossRef](#)]
14. Teece, D.J.; Pisano, G.; Shuen, A. Dynamic Capabilities and Strategic Management. *Strateg. Manag. J.* **1997**, *18*, 509–533. [[CrossRef](#)]
15. Chen, Y.-S.; Lai, S.-B.; Wen, C.-T. The Influence of Green Innovation Performance on Corporate Advantage in Taiwan. *J. Bus. Ethics* **2006**, *67*, 331–339. [[CrossRef](#)]
16. Chiou, T.-Y.; Chan, H.K.; Lettice, F.; Chung, S.H. The Influence of Greening the Suppliers and Green Innovation on Environmental Performance and Competitive Advantage in Taiwan. *Transp. Res. Part E Logist. Transp. Rev.* **2011**, *47*, 822–836. [[CrossRef](#)]
17. Xu, Y.; Yuan, L.; Khalfoui, R.; Radulescu, M.; Mallek, S.; Zhao, X. Making Technological Innovation Greener: Does Firm Digital Transformation Work? *Technol. Forecast. Soc. Change* **2023**, *197*, 122928. [[CrossRef](#)]
18. Li, K.; Ji, S. *Structural Analysis of the Chinese Framework for Digital Literacy of Teachers: Based on PLS-SEM*; Atlantis Press: Paris, France, 2024; pp. 205–210.
19. Khan, A. Disentangling the Empirical Insights into Job Satisfaction, Organizational Commitment, and Job Performance Nexus: A Mediated Model Tested Using PLS-SEM. *J. Inf. Manag. Libr. Stud.* **2024**, *7*, 140–164.
20. Popescu, I.A.; Reis Mourão, P.J. Exploring the Nexus between National Innovation Performance and Happiness. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 960. [[CrossRef](#)]
21. Alnor, N.H.A.; Al-Matari, E.M.; Mohammed, O.A.A.; Eltahir, I.A.E.; Eisa, M.I.A. The Impact of Artificial Intelligence in Improving the Efficiency of Financial Analysis. *Cogent Bus. Manag.* **2026**, *13*, 2651475. [[CrossRef](#)]
22. Chang, C.-H. The Influence of Corporate Environmental Ethics on Competitive Advantage: The Mediation Role of Green Innovation. *J. Bus. Ethics* **2011**, *104*, 361–370. [[CrossRef](#)]
23. Henseler, J.; Hubona, G.; Ray, P.A. Using PLS Path Modeling in New Technology Research: Updated Guidelines. *Ind. Manag. Data Syst.* **2016**, *116*, 2–20. [[CrossRef](#)]
24. Hair, J.F.; Risher, J.J.; Sarstedt, M.; Ringle, C.M. When to Use and How to Report the Results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24. [[CrossRef](#)]
25. Richter, N.F.; Hauff, S.; Ringle, C.M.; Gudergan, S.P. The Use of Partial Least Squares Structural Equation Modeling and Complementary Methods in International Management Research. *Manag. Int. Rev.* **2022**, *62*, 449–470. [[CrossRef](#)]
26. Richter, N.F.; Schubring, S.; Hauff, S.; Ringle, C.M.; Sarstedt, M. When Predictors of Outcomes Are Necessary: Guidelines for the Combined Use of PLS-SEM and NCA. *Ind. Manag. Data Syst.* **2020**, *120*, 2243–2267. [[CrossRef](#)]
27. Hambrick, D.C.; Mason, P.A. Upper Echelons: The Organization as a Reflection of Its Top Managers. *Acad. Manag. Rev.* **1984**, *9*, 193–206. [[CrossRef](#)] [[PubMed](#)]
28. Akter, S.; Wamba, S.F.; Gunasekaran, A.; Dubey, R.; Childe, S.J. How to Improve Firm Performance Using Big Data Analytics Capability and Business Strategy Alignment? *Int. J. Prod. Econ.* **2016**, *182*, 113–131. [[CrossRef](#)]
29. Gupta, M.; George, J.F. Toward the Development of a Big Data Analytics Capability. *Inf. Manag.* **2016**, *53*, 1049–1064. [[CrossRef](#)]
30. Li, L.; Su, F.; Zhang, W.; Mao, J.-Y. Digital Transformation by SME Entrepreneurs: A Capability Perspective. *Inf. Syst. J.* **2018**, *28*, 1129–1157. [[CrossRef](#)]
31. Brous, P.; Janssen, M.; Herder, P. The Dual Effects of the Internet of Things (IoT): A Systematic Review of the Benefits and Risks of IoT Adoption by Organizations. *Int. J. Inf. Manag.* **2020**, *51*, 101952. [[CrossRef](#)]
32. Davenport, T.H.; Ronanki, R. Artificial Intelligence for the Real World. *Harv. Bus. Rev.* **2018**, *96*, 108–116.
33. Hair, J.F.; Sarstedt, M.; Ringle, C.M.; Sharma, P.N.; Liengaard, B.D. Going beyond the Untold Facts in PLS-SEM and Moving Forward. *Eur. J. Mark.* **2024**, *58*, 81–106. [[CrossRef](#)]
34. Tseng, M.-L.; Chiu, A.S.F.; Tan, R.R.; Siriban-Manalang, A.B. Sustainable Consumption and Production for Asia: Sustainability through Green Design and Practice. *J. Clean. Prod.* **2013**, *40*, 1–5. [[CrossRef](#)]
35. Liu, Z.; Li, X.; Peng, X.; Lee, S. Green or Nongreen Innovation? Different Strategic Preferences among Subsidized Enterprises with Different Ownership Types. *J. Clean. Prod.* **2020**, *245*, 118786. [[CrossRef](#)]
36. Vasileiou, E.; Georgantzis, N.; Attanasi, G.; Llerena, P. Green Innovation and Financial Performance: A Study on Italian Firms. *Res. Policy* **2022**, *51*, 104530. [[CrossRef](#)]
37. Porter, M.E. *Competitive Advantage: Creating and Sustaining Superior Performance*; Simon and Schuster: New York, NY, USA, 2008; ISBN 978-1-4165-9584-7.
38. Luo, Y. Industrial Dynamics and Managerial Networking in an Emerging Market: The Case of China. *Strateg. Manag. J.* **2003**, *24*, 1315–1327. [[CrossRef](#)]
39. Lindell, M.K.; Whitney, D.J. Accounting for Common Method Variance in Cross-Sectional Research Designs. *J. Appl. Psychol.* **2001**, *86*, 114–121. [[CrossRef](#)] [[PubMed](#)]
40. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [[CrossRef](#)] [[PubMed](#)]

41. Hair, J.; Alamer, A. Partial Least Squares Structural Equation Modeling (PLS-SEM) in Second Language and Education Research: Guidelines Using an Applied Example. *Res. Methods Appl. Linguist.* **2022**, *1*, 100027. [[CrossRef](#)]
42. Shmueli, G.; Sarstedt, M.; Hair, J.F.; Cheah, J.-H.; Ting, H.; Vaithilingam, S.; Ringle, C.M. Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict. *Eur. J. Mark.* **2019**, *53*, 2322–2347. [[CrossRef](#)]
43. Li, S.; Gao, L.; Han, C.; Gupta, B.; Alhalabi, W.; Almakdi, S. Exploring the Effect of Digital Transformation on Firms' Innovation Performance. *J. Innov. Knowl.* **2023**, *8*, 100317. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.