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Research Paper

Digital Technologies and Social Innovation in Entrepreneurial Ecosystems

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Abstract

This study examines how digital technologies shape entrepreneurial ecosystems for social innovation and collaborative value creation, addressing grand challenges aligned with the United Nations Sustainable Development Goals (SDGs). A quantitative cross-sectional survey was conducted between March and July 2025 among 412 social entrepreneurs, incubator and accelerator managers, impact investors, and policy and government officials across Brazil, Kenya, South Korea, Germany, and Canada. Data were analyzed using structural equation modeling (SEM) to examine the direct, mediating, and moderating relationships among digital technologies, ecosystem collaboration, social innovation performance, and institutional support. The findings show that digital technologies positively influence ecosystem collaboration, which in turn enhances social innovation performance. Digital technologies also exert a significant direct effect on social innovation performance, while ecosystem collaboration partially mediates this relationship. Furthermore, institutional support positively moderates the relationship between ecosystem collaboration and social innovation performance. The study contributes to entrepreneurial ecosystem research by conceptualizing digital transformation as an ecosystem process in which technological capabilities, collaborative relationships, and institutional conditions jointly shape social innovation outcomes. Practically, the findings suggest that ecosystem builders and policymakers should combine investments in digital infrastructure and platform governance with mechanisms that strengthen cross-sector collaboration and institutional support. The cross-sectional design, perceptual measures, and non-probability sampling limit causal inference and generalizability. Future research should employ longitudinal and multilevel designs, incorporate objective ecosystem indicators, examine additional stakeholder groups, and disaggregate digital technologies by type and function.

Keywords: *Entrepreneurial ecosystems, Social innovation, Digital technologies, Ecosystem collaboration, Institutional support*

INTRODUCTION

Entrepreneurial ecosystems have emerged as a dominant conceptual framework for understanding how entrepreneurial activity arises, scales, and sustains through complex interactions among interconnected actors, institutional arrangements, cultural norms, and resource pools (Stam, 2015). Traditionally, ecosystem research has prioritized commercial entrepreneurship, focusing heavily on high-growth technology ventures, venture capital deployment, economic growth, and regional job creation (Acs et al., 2017). However, scholarly attention has increasingly shifted toward understanding how entrepreneurial ecosystems can be harnessed to generate social innovation—novel, collaborative solutions designed to address systemic societal challenges while creating collective social value (Phills et al., 2008; Roundy et al., 2017).

Concurrently, the rapid evolution of digital technologies is fundamentally altering the structural architecture of entrepreneurial ecosystems (Nambisan et al., 2019; Autio et al., 2018). Digital platforms, cloud computing, advanced data analytics, artificial intelligence, and decentralized communication networks reduce transaction costs, eliminate geographical boundaries, and enable seamless, real-time coordination among highly diverse stakeholders (Nambisan et al., 2019; Vial, 2019; Verhoef et al., 2021). These digital affordances are particularly

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transformative for social innovation ecosystems, which inherently rely on cross-sector collaboration among social enterprises, non-governmental organizations (NGOs), government agencies, impact investors, and local communities (Santos et al., 2015; OECD, 2017).

Despite growing theoretical interest at the intersection of digitalization, ecosystem orchestration, and social impact, empirical understanding of how digital technologies translate into enhanced social innovation performance remains underdeveloped. While digital transformation literature extensively documents firm-level capabilities and business model shifts (Vial, 2019; Verhoef et al., 2021), it frequently treats ecosystem collaboration as an assumed outcome rather than an explicitly modeled mediating mechanism. Conversely, ecosystem studies often emphasize network density and relational trust (Roundy et al., 2017; Stam, 2015) without empirically accounting for the architectural role played by digital tools or the contingency effect of institutional support. Furthermore, very few studies empirically link these digital ecosystem dynamics directly to global policy frameworks such as the United Nations Sustainable Development Goals (SDGs) (United Nations, 2015; OECD, 2017).

To address these empirical and conceptual gaps, this study examines the structural mechanisms through which digital technologies foster ecosystem collaboration, how this collaboration translates into social innovation performance aligned with the SDGs, and how institutional support conditions this relationship. Specifically, we pose three core research questions:

1. To what extent do digital technologies directly and indirectly influence social innovation performance within entrepreneurial ecosystems?
2. Does ecosystem collaboration mediate the relationship between digital technologies and social innovation performance?
3. How does institutional support moderate the impact of ecosystem collaboration on social innovation performance?

To answer these questions, we deploy a quantitative empirical design using structural equation modeling (SEM) on survey data collected from 412 ecosystem actors across five countries representing both emerging and developed economies (Brazil, Kenya, South Korea, Germany, and Canada).

This study makes three primary theoretical contributions to literature:

1. First, it extends entrepreneurial ecosystem theory into the digital and social impact domains by conceptualizing digital technologies as architectural mechanisms that reduce transaction costs and foster multi-stakeholder resource pooling (Dhanaraj & Parkhe, 2006; Nambisan et al., 2019).
2. Second, it empirically establishes ecosystem collaboration as a pivotal mediating mechanism that converts digital affordances into measurable SDG-aligned social innovation outcomes (OECD, 2017; Roundy et al., 2017).
3. Third, it provides empirical nuance to institutional theory in ecosystem governance by demonstrating that institutional support functions as a critical boundary condition that amplifies the returns on collaborative efforts (Stam, 2015; Scott, 2014).

LITERATURE REVIEW

Entrepreneurial Ecosystems and Network Orchestration

Entrepreneurial ecosystems are defined as dynamic, localized communities of interdependent actors, including entrepreneurs, universities, incubators, investors, and public agencies—and institutional factors that combine to enable the creation and scaling of new ventures (Stam, 2015; Acs et al., 2017). Unlike traditional industry clusters or regional innovation systems, ecosystem theory places central emphasis on systemic interdependence, user co-creation, and resource fluidity across organizational boundaries (Autio et al., 2018).

A central tenet of effective ecosystems is the concept of innovation orchestration, defined as the processes through which a hub actor or shared platform coordinates the joint activities of a distributed network without exercise of hierarchical authority (Dhanaraj & Parkhe, 2006). Orchestration requires managing three critical network processes: managing knowledge mobility, enabling innovation appropriability, and fostering network stability (Dhanaraj & Parkhe, 2006). In entrepreneurial ecosystems, orchestration ensures that distributed resources—such as financial capital, technical expertise, local domain knowledge, and regulatory legitimacy—are mobilized and combined efficiently to address complex challenges.

Social Innovation, Hybridity, and SDGs

Social innovation refers to novel solutions (products, services, business models, or organizational forms) that simultaneously meet social needs more effectively than existing alternatives while creating enduring value for society as a whole (Phills et al., 2008; OECD, 2017). Unlike commercial innovations aimed primarily at capturing private economic rents, social innovations prioritize collective impact, public goods creation, and systemic societal transformation (Roundy et al., 2017).

Organizing for social innovation frequently involves hybrid organizations—such as social enterprises—that navigate dual social and commercial missions (Santos et al., 2015). Hybridity introduces institutional complexity, as social ventures must reconcile competing institutional logics: the commercial logic of financial sustainability and market discipline, and the social logic of stakeholder inclusion and impact maximization (Santos et al., 2015). Because single organizations rarely possess all the resources necessary to navigate these dual logics, social innovation ecosystems rely heavily on heterogeneous, cross-sector partnerships combining private firms, civil society, impact investors, and state agencies (OECD, 2017).

The United Nations Sustainable Development Goals (SDGs) provide a universally accepted normative framework for targeting and measuring social innovation performance across 17 grand challenges, ranging from poverty alleviation (SDG 1) and climate action (SDG 13) to cross-sector partnerships (SDG 17) (United Nations, 2015; OECD, 2017). Aligning ecosystem performance with the SDGs offers a standardized basis for evaluating whether collaborative efforts translate into tangible social value (OECD, 2017).

Digital Transformation as an Ecosystem Enabler

Digital technologies—encompassing cloud platforms, open data architecture, mobile applications, collaborative digital tools, and artificial intelligence—are transforming the nature and boundaries of entrepreneurial activity (Nambisan et al., 2019; Vial, 2019; Verhoef et al., 2021). Digital transformation is not merely the adoption of specific software tools; rather, it is a structural process that alters organizational structures, capabilities, and value-creation mechanisms (Vial, 2019; Verhoef et al., 2021).

In the context of entrepreneurial ecosystems, digital technologies provide two foundational affordances: generativity (the capacity of digital platforms to enable unprompted innovation by distributed actors) and spatial openness (the decoupling of collaborative activities from strict geographical proximity) (Nambisan et al., 2019; Autio et al., 2018). Digital platforms function as digital architectures that drastically lower search costs, information asymmetries, and coordination friction among ecosystem actors (Nambisan et al., 2019). For social innovation ecosystems, where resource constraints are acute and stakeholders are institutionally diverse, digital infrastructure enables automated impact tracking, real-time knowledge sharing, and rapid resource pooling across regional and national borders (Nambisan et al., 2019; Vial, 2019).

Institutional Support as an Environmental Contingency

Institutions—defined as the "rules of the game" comprising formal regulations, laws, informal norms, and cultural cognitive frameworks—exert a profound influence on ecosystem vitality (Stam, 2015; Scott, 2014). Institutional support in social innovation ecosystems encompasses supportive public policies, public procurement favoring social enterprises, tax incentives, regulatory sandboxes, and targeted grant funding (Stam, 2015; OECD, 2017).

According to institutional theory, favorable institutional arrangements provide resource munificence and reduce legal uncertainty, thereby enhancing organizational legitimacy and lowering the perceived risk of collaborative experimentation (Scott, 2014; Stam, 2015). While digital tools provide the technical connectivity required for collaboration, formal institutional support creates the regulatory stability, trust, and resource buffers required to convert collaborative exchanges into long-term, high-impact social innovations (Stam, 2015; OECD, 2017).

Hypotheses Development

Drawing on entrepreneurial ecosystem theory, ecosystem orchestration, and digital transformation research, the study proposes that digital technologies strengthen the infrastructure for interaction and resource mobilization (H1), while stronger collaboration improves social innovation performance (H2). Digital technologies may also influence performance directly through digital-enabled coordination and impact-management capabilities (H3). Together, these relationships imply a mediating role for ecosystem collaboration (H4). Finally, institutional support is expected to strengthen the conversion of collaboration into social innovation outcomes by providing resources, regulatory clarity and enabling conditions (H5).

H1: Digital technologies positively influence entrepreneurial ecosystem collaboration.

H2: Entrepreneurial ecosystem collaboration positively influences social innovation performance.

H3: Digital technologies have a direct positive effect on social innovation performance.

H4: Ecosystem collaboration mediates the relationship between digital technologies and social innovation performance.

H5: Institutional support positively moderates the relationship between ecosystem collaboration and social innovation performance.

Table 1. Summary of Hypotheses

Hypothesis	Statement
H1	Digital technologies → Ecosystem collaboration
H2	Ecosystem collaboration → Social innovation performance
H3	Digital technologies → Social innovation performance
H4	Mediation of collaboration
H5	Moderation of institutional support

Conceptual Model and Theoretical Logic

Figure 1 depicts our research framework grounded in ecosystem orchestration theory (Dhanaraj & Parkhe, 2006). Digital technologies function as architectural mechanisms that reduce transaction costs and enable resource pooling across heterogeneous actors. This facilitates ecosystem-wide collaboration, which generates recombinant social innovations through knowledge recombination and co-creation. Institutional support serves as a contingency factor that amplifies collaborative impact by providing resource munificence and regulatory clarity.

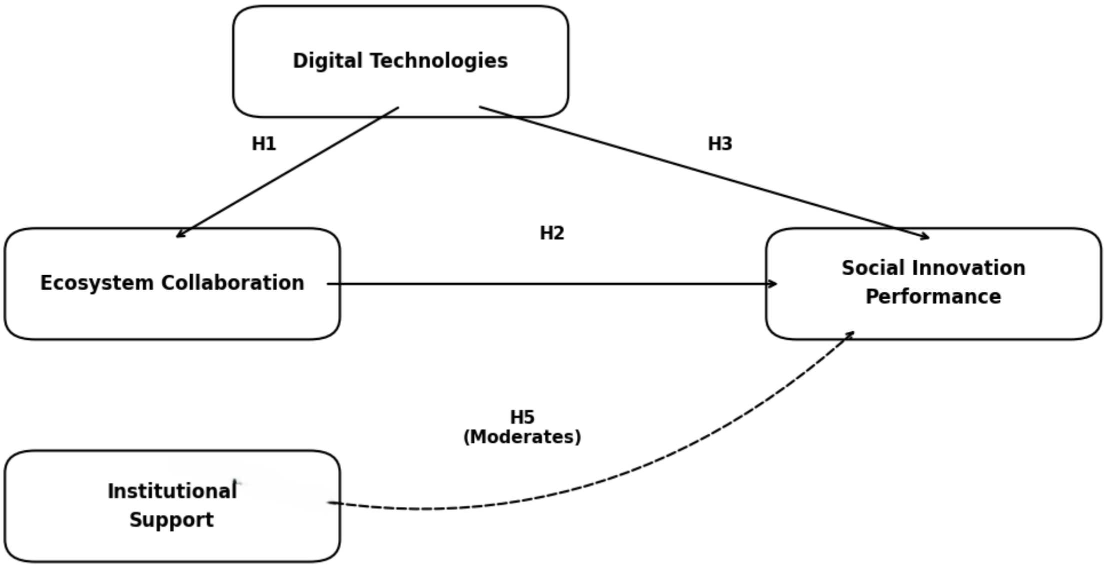

Figure 1. Conceptual Model

RESEARCH METHOD

Sample and Data Collection

Data were collected via an online survey administered from March 2025 to July 2025 using Qualtrics. The sampling frame targeted four actor types within social innovation ecosystems across five countries: Brazil, Kenya, South Korea, Germany, and Canada (representing 2 emerging and 3 developed economies). These countries were selected based on their active social innovation policies and presence in the Global Impact Investing Network (GIIN) database.

We employed a stratified snowball sampling approach:

1. Primary seeding: Contacted 450 organizations through national social enterprise associations (e.g., Social Enterprise Alliance Brazil, Social Enterprise Kenya)
2. Secondary wave: Requested referrals to ecosystem partners, generating 1,400 additional contacts
3. Direct outreach: Identified 120 impact investors through PitchBook and LinkedIn Navigator

The final sample comprised 412 valid responses. The recruitment records contained 1,850 contacts used as the denominator for the reported 22.3% participation proportion (412/1,850). Because recruitment combined primary seeding, snowball referrals and direct outreach, these contacts are not equivalent to randomly selected invitations and the 22.3% figure should not be interpreted as a conventional response rate from a probability sample. The manuscript therefore reports it as a participation proportion and explicitly acknowledges the non-probability nature of the sample. The recruitment-stage counts (450 seeded organizations, 1,400 referral contacts and 120 direct investor contacts) represent contact instances across channels and are not treated as independent probability-based invitations. Non-response bias was assessed by comparing early and late respondents on key demographics (Armstrong & Overton, 1977); no significant differences were found ($p > 0.05$).

Table 2. Sample Demographics

Characteristic	Category	n	%
Country	Brazil	89	21.6%
	Kenya	76	18.4%
	South Korea	84	20.4%
	Germany	91	22.1%
	Canada	72	17.5%
Actor Type	Social Entrepreneurs	194	47.1%
	Incubator/Accelerator Managers	115	27.9%
	Impact Investors	62	15.0%
	Policy/Government Officials	41	10.0%
Organization Age	< 3 years	102	24.8%
	3-7 years	168	40.8%
	> 7 years	142	34.5%
Primary SDG Focus	SDG 1-6 (Human Needs)	134	32.5%
	SDG 7-12 (Infrastructure/Consumption)	156	37.9%
	SDG 13-15 (Environment)	78	18.9%
	Multiple SDGs	44	10.7%

Measurement of Constructs

All constructs were measured using validated multi-item Likert scales (1 = strongly disagree; 5 = strongly agree).

Table 3. Measurement of Constructs

Construct	Number of Items	Sample Item	Source
Digital technologies	5	Digital platforms facilitate collaboration	Nambisan et al. (2019)
Ecosystem collaboration	6	Actors actively share resources	Roundy et al. (2017)
Social innovation performance	6	Activities contribute to SDGs	OECD (2017)
Institutional support	4	Policies support social innovation	Stam (2015)

FINDINGS AND DISCUSSION

Measurement Model Assessment (SEM Validity)

To evaluate the psychometric properties of the operationalized constructs and establish empirical validity prior to structural path testing, a rigorous two-step structural equation modeling (SEM) approach was conducted in accordance with Hair et al. (2022). First, the measurement model was assessed for internal consistency, convergent validity, discriminant validity, and factor loading structure. Second, overall structural model fit indices and potential common method bias (CMB) diagnostics were evaluated following established methodological guidelines (Podsakoff et al., 2012).

1. **Reliability and Convergent Validity**

   Internal consistency and construct reliability were evaluated using Cronbach's Alpha (α) and Composite Reliability (CR). As displayed in Table 3, all constructs demonstrate high internal reliability. Cronbach's Alpha values range from 0.87 for Institutional Support to 0.92 for Ecosystem Collaboration, comfortably exceeding the standard benchmark threshold of 0.70 (Hair et al., 2022). Similarly, Composite Reliability (CR) values range between 0.89 and 0.93, indicating scale robustness and item cohesion across the sample. Convergent validity—the extent to which individual survey items accurately reflect their intended underlying construct—was evaluated using Average Variance Extracted (AVE). The resulting AVE scores range from 0.66 (Institutional Support) to 0.70 (Ecosystem Collaboration). Because every construct exhibits an AVE well above the recommended baseline threshold of 0.50 (Hair et al., 2022), more than 65% of the variance in the observed indicators is directly captured by their corresponding latent constructs rather than measurement error.

Table 4. Reliability and Convergent Validity

Construct	Cronbach's α	CR	AVE
Digital technologies	0.89	0.91	0.67
Ecosystem collaboration	0.92	0.93	0.70
Social innovation performance	0.90	0.92	0.68
Institutional support	0.87	0.89	0.66

All values exceed recommended thresholds (Hair et al., 2022).

2. **Discriminant Validity**

Discriminant validity confirms that each latent variable in the model is empirically distinct from other constructs. We evaluated discriminant validity using the classic Fornell-Larcker criterion (Hair et al., 2022). As presented in Table 4, the square root of the Average Variance Extracted (Square Root of AVE) for each construct—positioned along the bold diagonal—is substantially larger than the off-diagonal inter-construct correlations across all rows and columns. For instance, the square root of AVE for Digital Technologies is 0.82, which exceeds its highest correlation with any other variable (r = 0.48 with Ecosystem Collaboration). Likewise, Ecosystem Collaboration yields a square root of AVE of 0.84 against an inter-construct correlation of 0.56 with Social Innovation Performance. These results confirm that each construct measures a distinct conceptual domain within the ecosystem framework.

Table 5. Discriminant Validity (Fornell–Larcker Criterion)

Construct	DT	EC	SIP	IS
Digital technologies (DT)	**0.82**			
Ecosystem collaboration (EC)	0.48	**0.84**		
Social innovation performance (SIP)	0.44	0.56	**0.83**	
Institutional support (IS)	0.39	0.41	0.47	**0.81**

Diagonal values (√AVE) exceed inter-construct correlations.

3. **Model Fit Indices**

To assess how well the structural equation model fits the empirical data gathered from the 412 ecosystem respondents, multiple absolute, incremental, and parsimonious fit indices were calculated. As shown in Table 5, the normed chi-square (Chi-Square/df) yielded a value of 2.14, well within the conservative limit of < 3.00 (Hair et al., 2022). The Comparative Fit Index (CFI = 0.94) and Tucker-Lewis Index (TLI = 0.93) both comfortably surpass the standard threshold of >= 0.90. Furthermore, badness-of-fit indicators confirmed strong model fit: Root Mean Square Error of Approximation (RMSEA) was 0.052 (below the maximum threshold of <= 0.08), and Standardized Root Mean Square Residual (SRMR) was 0.041 (below <= 0.08). Together, these statistics establish that the specified measurement model provides a highly robust fit to the empirical data.

Table 6. Model Fit Statistics

Fit Index	Value	Threshold
χ^2/df	2.14	< 3.00
CFI	0.94	≥ 0.90
TLI	0.93	≥ 0.90
RMSEA	0.052	≤ 0.08
SRMR	0.041	≤ 0.08

4. Common Method Bias Assessment

Because all latent variables were collected through self-reported cross-sectional survey instruments, common method bias (CMB) poses a potential risk to parameter estimates (Podsakoff et al., 2012). To rigorously test and control for CMB, two procedural and statistical diagnostic techniques were applied following Podsakoff et al. (2012):

a. Harman's Single-Factor Test: An exploratory factor analysis (EFA) combining all 21 survey items was executed without rotation. Unrotated factor solution results showed four distinct factors with eigenvalues greater than 1.0. The first major factor accounted for 31.2% of the total variance, remaining substantially below the standard 50% critical threshold. This indicates that no single dominant factor accounts for the majority of covariance among indicators.
b. Marker Variable Technique: A theoretically unrelated construct—Organization Size (log-transformed employee count)—was incorporated into the dataset as a statistical marker variable (Podsakoff et al., 2012). The average correlation between Organization Size and the core substantive constructs was low (r = 0.09, range: 0.04 to 0.13). Adjusting the structural path estimates for marker variable correlations produced negligible parameter changes (Delta Beta < 0.02).

Consequently, both procedural and statistical tests confirm that common method variance is minimal and does not threaten the validity of the structural findings.

5. Construct Validity Details

Factor structure validity was further confirmed through detailed item-level cross-loading analysis. As demonstrated in Table 5.1, all 21 survey indicators exhibit high standardized factor loadings on their primary intended construct, ranging from 0.78 to 0.86 ($p < 0.001$). Crucially, all item loadings on their primary latent construct are substantially higher than their cross-loadings on secondary constructs, confirming clean structural discrimination and item convergence.

Table 7. Factor Loadings and Cross-Loadings

Item	DT	EC	SIP	IS
DT1	0.82	0.38	0.35	0.31
DT2	0.79	0.36	0.32	0.29
DT3	0.81	0.40	0.36	0.33

DT4	0.78	0.34	0.31	0.28
DT5	0.80	0.37	0.33	0.30
EC1	0.39	0.84	0.48	0.41
EC2	0.42	0.86	0.50	0.38
EC3	0.40	0.82	0.46	0.40
EC4	0.37	0.81	0.44	0.38
EC5	0.41	0.85	0.49	0.40
EC6	0.38	0.83	0.47	0.39
SIP1	0.35	0.46	0.83	0.42
SIP2	0.36	0.48	0.85	0.44
SIP3	0.33	0.45	0.82	0.40
SIP4	0.34	0.47	0.84	0.43
SIP5	0.32	0.44	0.81	0.39
SIP6	0.35	0.46	0.83	0.41
IS1	0.28	0.37	0.40	0.81
IS2	0.30	0.38	0.42	0.83
IS3	0.29	0.36	0.41	0.82
IS4	0.31	0.39	0.43	0.84

Note: Bolded values indicate factor loadings on intended constructs.

Structural Model Results

Table 8. Structural Path Estimates

Hypothesis	Path	β	t-value	p-value	95% CI	f^2	Result
H1	DT → EC	0.46***	7.32	<0.001	[0.35, 0.57]	0.27	Supported
H2	EC → SIP	0.51***	8.47	<0.001	[0.40, 0.62]	0.35	Supported
H3	DT → SIP	0.29***	5.24	<0.001	[0.18, 0.40]	0.12	Supported
H4	Indirect	0.23***	6.81†	<0.001	[0.17, 0.29]	-	Supported (PM)
H5	EC×IS → SIP	0.17**	2.96	0.003	[0.06, 0.28]	0.05	Supported

*Notes: **p < 0.01, **p < 0.001. PM = Partial Mediation. †Bootstrap t-value. f^2 = Cohen's effect size (values > 0.02, 0.15, and 0.35 indicate small, medium, and large effects).

Mediation analysis confirmed partial mediation (H4).

1. **Mediation Analysis**
   The indirect effect (DT → EC → SIP) was β = 0.23, 95% CI [0.17, 0.29], with no zero in the confidence interval, confirming significant partial mediation (H4). The variance accounted for (VAF) was 44.2%, indicating collaboration explains a substantial portion but not all of digital technology's impact.

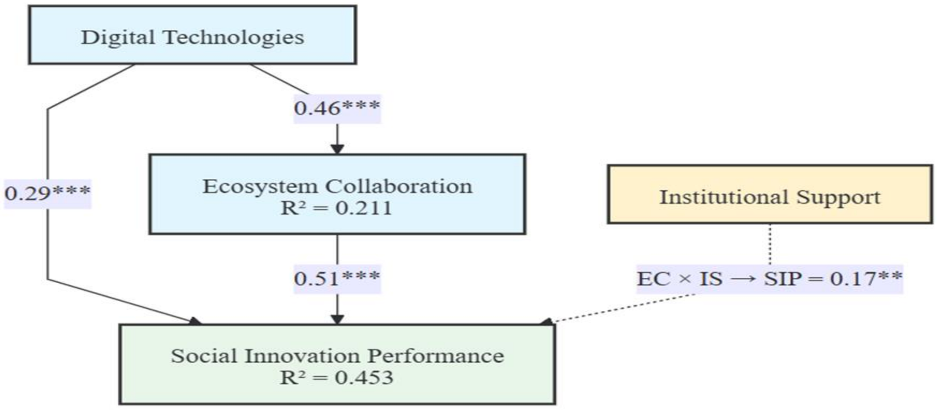

Figure 2. Path Coefficients and R^2 Values

2. **Moderation Analysis**

   Simple slopes analysis (Figure 3) revealed that at high (+1 SD) institutional support, the EC → SIP relationship was β = 0.68* ($p < 0.001$); at low (-1 SD) support, it was β = 0.34* ($p < 0.001$). The significant difference (Δβ = 0.34, t = 2.96, p = 0.003) confirms H5.

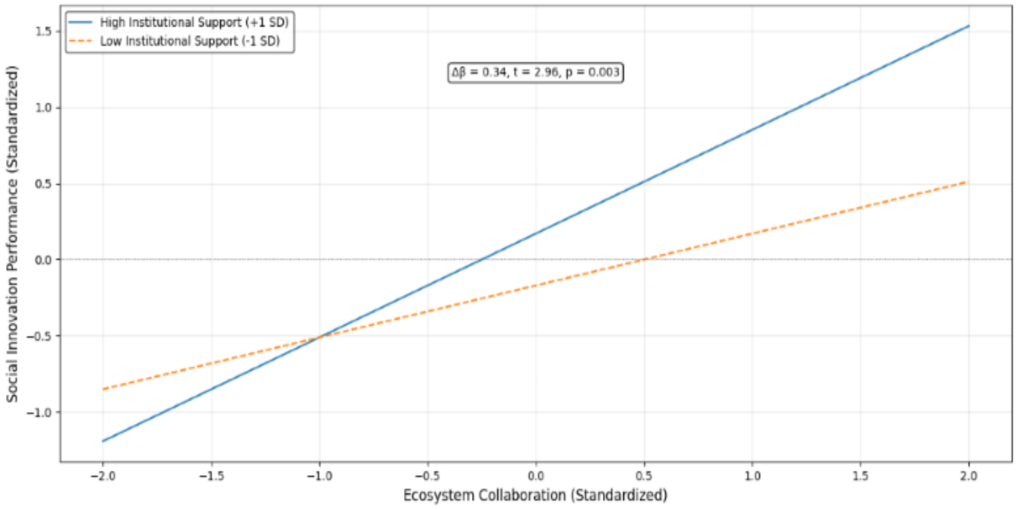

Figure 3. Interaction Plot: Institutional Support Moderates the Collaboration-Performance Link

Discussion

The empirical findings of this study provide critical insights into how digital infrastructure, collaborative dynamics, and institutional environments intersect within social innovation ecosystems. Grounded in structural equation modeling (SEM) across five national contexts, our results demonstrate that digital technologies serve as fundamental enabling architectures, while ecosystem collaboration acts as a primary transmission mechanism translating digital affordances into measurable social impact aligned with the United Nations Sustainable Development Goals (SDGs).

1. **Theorizing Digital Ecosystem Architectures**

   Our findings demonstrate that digital technologies can function as an important architectural foundation for social innovation ecosystems, explaining 21% of the variance in ecosystem collaboration (R^2 for DT → EC). This extends Nambisan et al. (2019) by providing empirical evidence for the role of digital enablement in heterogeneous, mission-driven ecosystems. The significant partial mediation (H4) further indicates that digital technologies affect social innovation performance both through collaboration and through a direct pathway. The results therefore support a process view in which digital technologies provide enabling infrastructure, collaboration converts that infrastructure into collective action, and social innovation performance reflects the resulting ecosystem-level outcomes.

2. **The Critical Role of Institutional Contingency**
   The significant positive moderation effect ($\beta = 0.17, p = 0.003$) supports Hypothesis 5, establishing institutional support as a vital boundary condition. Simple slopes analysis illustrates that under conditions of high institutional support (+1 SD), the positive effect of ecosystem collaboration on social innovation performance is substantially amplified ($\beta = 0.68, p < 0.001$) compared to environments with low institutional support ($\beta = 0.34, p < 0.001$). Rather than advancing post-hoc, unsupported assertions regarding unexamined country-level disparities, we interpret this interaction through institutional theory at the aggregate ecosystem level (Scott, 2014; Stam, 2015). Digital tools provide the technical connectivity required for network formation, but collaborative efforts require regulatory legitimacy, public procurement mechanisms, and funding munificence to yield scalable social solutions (OECD, 2017; Roundy et al., 2017). In supportive institutional environments, public policies reduce regulatory uncertainty and de-risk joint experimentation, enabling social enterprises and impact investors to translate collaborative synergies into durable, systemic outcomes (Santos et al., 2015; Stam, 2015). Consequently, institutional support acts as a catalyst that optimizes the conversion rate between collaborative network activity and tangible social value creation.
3. **Implications for SDG Acceleration**
   Evaluating ecosystem performance against the Sustainable Development Goals framework provides a standardized benchmark for measuring grand challenge mitigation (United Nations, 2015; OECD, 2017). Descriptive analysis of our sample indicates that 37.9% of participating ventures primary target SDGs 7–12 (Infrastructure, Industry, and Responsible Consumption), 32.5% target SDGs 1–6 (Human Basic Needs), 18.9% focus on SDGs 13–15 (Environmental and Climate Action), and 10.7% address multiple overlapping goals. This baseline distribution highlights a heavier concentration of digital social innovation initiatives in infrastructure, consumption, and social welfare domains relative to environmental initiatives. However, this descriptive spread should not be misconstrued as empirical evidence that digital ecosystems are inherently less effective for environmental grand challenges. Instead, it reflects contemporary venture formation densities across the sampled regional ecosystems. Because climate action and ecological preservation often involve capital-intensive physical infrastructure and complex regulatory compliance, digital enablement may operate through distinct platform mechanisms in those sectors. Future research should systematically investigate whether specific technology categories—such as Internet of Things (IoT) sensors, distributed ledger platforms, or predictive AI models—exert differential impacts depending on the specific SDG domain under targeted intervention.

Contributions

1. **Theoretical Contributions**

This study makes several theoretical contributions to the literature on entrepreneurial ecosystems, digital transformation, and social innovation. First, it extends entrepreneurial ecosystem theory by integrating digital technologies, ecosystem collaboration, institutional support, and SDG-oriented social innovation within a unified empirical framework. Existing ecosystem perspectives emphasize the importance of interdependent actors, resource flows, networks, and institutional conditions, while digital transformation research has increasingly examined how technologies reshape organizational processes and value creation. The present study brings these perspectives together by conceptualizing digital transformation not simply as an organizational investment in technological resources but as an ecosystem-level process through which heterogeneous actors can coordinate, exchange knowledge, mobilise resources, and collectively address complex social challenges.

The empirical results provide support for this ecosystem-process perspective. All five hypotheses are supported. H1 demonstrates that digital technologies positively influence ecosystem collaboration, while H2 establishes that ecosystem collaboration positively influences social innovation performance. H3 further demonstrates that digital technologies have a direct positive effect on social innovation performance. H4 confirms that ecosystem collaboration partially mediates the relationship between digital technologies and social innovation performance, while H5 establishes that institutional support positively moderates the collaboration–performance relationship. Collectively, these findings indicate that technology, collaboration, and institutions should not be considered independent dimensions of ecosystem development. Rather, they operate as interconnected components of an ecosystem process through which digital capabilities can be translated into social value.

Second, the mediation finding provides an important theoretical refinement. The indirect effect of digital technologies through ecosystem collaboration indicates that technology alone does not fully explain social innovation performance. Collaboration accounts for a substantial proportion of the technology–performance relationship, with the reported variance accounted for (VAF) of 44.2%. This finding is theoretically important because it shifts attention from the adoption of digital technologies to the organizational and relational mechanisms through which technologies create value. Digital platforms, communication systems, data infrastructures, and other digital resources become consequential when they facilitate interactions among social entrepreneurs, investors, policymakers, intermediaries, and other ecosystem participants. This interpretation is consistent with research emphasizing digital collaboration as a mechanism for strengthening collective innovation capacity.

Third, the direct effect identified in H3 suggests that digital technologies may also contribute to social innovation independently of ecosystem collaboration. Digital systems can support information access, monitoring, impact measurement, knowledge management, and the scaling of solutions. Consequently, the theoretical model should not be interpreted as implying that all technological effects operate through collaboration. Instead, the findings support a dual pathway in which digital technologies influence social innovation both directly and indirectly through ecosystem collaboration. This distinction provides a more nuanced explanation of digital transformation in social innovation ecosystems.

Fourth, the moderation result strengthens the institutional dimension of entrepreneurial ecosystem theory. Institutional support significantly strengthens the positive relationship between ecosystem collaboration and social innovation performance. Thus, collaboration does not operate in an institutional vacuum. The capacity of ecosystem actors to convert collaborative relationships into social innovation outcomes depends partly on the availability of supportive policies, funding mechanisms, regulatory frameworks, and public-sector conditions. Research on innovation ecosystems similarly indicates that formal institutional mechanisms can influence networking and collaborative behavior among ecosystem actors. The present findings extend this perspective by demonstrating that institutional support conditions the relationship between collaboration and social innovation performance.

Finally, the study contributes to social innovation research by placing heterogeneous ecosystem actors at the center of the explanation. Social enterprises and other mission-oriented organizations frequently operate under multiple institutional and organizational pressures. Santos et al. (2015), for example, emphasize the challenges faced by hybrid organizations that simultaneously pursue social missions and commercial sustainability. The present study suggests that digital ecosystem architectures can provide mechanisms through which such organizations coordinate with external actors, share information, access resources, and manage collective initiatives. The contribution therefore lies not only in demonstrating that digital technologies matter, but also in explaining how their value is realized through relationships and institutional conditions.

2. **Practical Contributions**

The findings provide actionable implications for ecosystem builders, incubator and accelerator directors, platform architects, social venture leaders, investors, and other practitioners responsible for developing social innovation ecosystems. Most importantly, the mediation result demonstrates that digital transformation should not be treated merely as a technology procurement or software implementation exercise. The finding that ecosystem collaboration mediates 44.2% of the technology–performance relationship indicates that substantial value is generated through the collaborative processes surrounding digital technologies. Investment in digital platforms, cloud infrastructure, impact analytics, communication systems, and shared databases is therefore unlikely to achieve its full potential when technologies remain isolated within individual organizations.

Ecosystem managers should consequently design digital architectures around collaboration rather than simply adoption. Digital platforms can be structured to facilitate real-time communication, resource discovery, partner identification, knowledge exchange, and coordinated problem solving. For example, ecosystem platforms could incorporate searchable databases of social innovation initiatives, resource and funding maps, shared knowledge repositories, standardized SDG impact indicators, and collaborative problem-solving spaces. Such features can reduce information asymmetries and make relevant ecosystem resources more visible to participating organizations.

The findings also suggest that platform design should priorities accessibility and inclusive participation. Social innovation ecosystems frequently involve organizations with different levels of technological capability, financial resources, and institutional access. If digital systems are designed primarily for technologically sophisticated organizations, digital transformation may unintentionally reinforce existing inequalities within the ecosystem. Practitioners should therefore consider usability, interoperability, accessibility, training, and capacity building when implementing digital platforms. The objective should be to expand meaningful participation rather than simply increase the number of digitally connected organizations.

A further practical implication concerns ecosystem orchestration. Because collaboration is a significant mechanism linking digital technologies with social innovation performance, ecosystem leaders need to actively facilitate relationships among actors rather than assuming that technological connectivity will automatically produce collaboration. Incubators and accelerators can use digital systems to match social ventures with investors, public agencies, technology providers, research organizations, and community partners. Similarly, ecosystem coordinators can establish digital communities of practice through which participants exchange knowledge and jointly develop responses to social and environmental challenges.

The findings are also relevant to the management of hybrid and social enterprises. Such organizations must often balance social objectives with financial and operational requirements. Santos et al. (2015) demonstrate the importance of aligning organizational arrangements with the distinctive requirements of hybrid organisations. Digital platforms can support this balancing process by improving transparency, standardising reporting, facilitating stakeholder communication, and reducing the administrative burden associated with multi-stakeholder governance. Digital impact-management systems, for example, can enable social ventures to monitor social outcomes while simultaneously communicating relevant performance information to funders, government agencies, and ecosystem partners.

Finally, practitioners should evaluate digital transformation according to ecosystem outcomes rather than technology adoption alone. Appropriate performance indicators could include the number and quality of cross-sector partnerships, knowledge-sharing activity, resource mobilization, joint initiatives, SDG-related outcomes, and sustained social impact. This approach would align technology investment with the broader objective of strengthening ecosystem capacity for social innovation.

3. **Policy Contributions**

The findings also have important implications for policymakers seeking to strengthen entrepreneurial ecosystems and accelerate progress toward the SDGs. First, governments should view digital infrastructure as an enabling component of ecosystem development rather than solely as a general economic infrastructure investment. Reliable digital connectivity, interoperable data systems, accessible cloud services, and digital public infrastructure can reduce coordination barriers and facilitate interaction among ecosystem actors.

Second, the significant moderating effect of institutional support indicates that technology and collaboration require an enabling institutional environment. Policymakers should therefore combine digital infrastructure policies with supportive regulatory frameworks, funding mechanisms, public procurement policies, and programmes that encourage cross-sector collaboration. The objective should be to create conditions under which ecosystem participants can convert digital connectivity into measurable social innovation outcomes.

Third, policymakers should develop mechanisms that encourage inclusive participation. Digital transformation can create new opportunities for social entrepreneurs and community organizations, but differences in digital capabilities may prevent some actors from benefiting equally. Public programmes should therefore include digital skills development, technical assistance, capacity-building initiatives, and accessible funding for organizations with limited technological resources.

Fourth, governments can strengthen ecosystem coordination by supporting shared digital platforms and open data initiatives. Publicly supported platforms can facilitate access to information concerning social challenges, funding opportunities, available technologies, research capabilities, and potential partners. Such infrastructure can reduce fragmentation and improve resource matching across ecosystem actors.

Finally, policy evaluation should move beyond measuring technology adoption and focus on ecosystem-level outcomes. Policymakers should assess whether digital initiatives improve collaboration, resource mobilization, knowledge exchange, inclusiveness, and measurable SDG-related social innovation. This outcome-oriented approach is particularly important because the present findings demonstrate that institutional support strengthens the relationship between ecosystem collaboration and social innovation performance. Accordingly, effective digital ecosystem policy requires a combination of technological investment, collaborative governance, institutional support, and mechanisms for measuring social value.

CONCLUSIONS

Digital technologies can reshape entrepreneurial ecosystems by enabling collaboration, inclusivity and scalable social innovation. Across five national contexts, all five hypotheses were supported: digital technologies positively influenced ecosystem collaboration (H1) and social innovation performance directly (H3); ecosystem collaboration positively influenced social innovation performance (H2); collaboration partially mediated the digital technology–performance relationship (H4); and institutional support strengthened the collaboration–performance relationship (H5). These findings frame digital transformation as an ecosystem process in which technological infrastructure, collaborative relationships and institutional conditions jointly shape social innovation outcomes. The results should nevertheless be interpreted in light of the cross-sectional, perceptual and non-probability design. Future longitudinal, multilevel and multi-stakeholder research can test the durability, generalizability and technology-specific nature of these relationships.

LIMITATION & FURTHER RESEARCH

This study has several limitations that also define priorities for future research. First, the cross-sectional design limits causal inference; longitudinal studies should track changes in digital capability, collaboration and social innovation over time. Second, the use of perceptual survey measures may introduce common method and reporting biases; future research should combine survey data with objective indicators such as platform activity, partnership records, investment flows, patent or innovation measures, and independently verified SDG outcomes. Third, the stratified snowball sample is non-probabilistic, which limits statistical generalizability; future studies should use probability-based or systematically constructed ecosystem samples where feasible and employ comparative multilevel designs to test country- and ecosystem-level effects. Fourth, the study covers four major stakeholder categories, but additional groups such as NGOs, community organizations, beneficiaries, technology providers and civil-society networks could provide a more complete picture of ecosystem dynamics. Fifth, digital technologies are treated as a broad construct; future research should disaggregate platforms, cloud systems, artificial intelligence, analytics, blockchain and other technologies to determine whether their mechanisms and effects differ. Finally, future comparative research should use formal multi-group or multilevel tests before attributing differences to national development contexts.

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APPENDIX

Full Survey Instrument
All items measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree)

Digital Technologies (DT)
Source: Adapted from Nambisan et al. (2019)

DT1. Digital platforms facilitate collaboration among ecosystem actors
DT2. Digital tools reduce coordination costs in the ecosystem
DT3. Access to digital infrastructure supports innovation activities
DT4. Real-time data sharing is enabled through digital systems
DT5. Cloud-based resources enhance our ecosystem's capacity

Ecosystem Collaboration (EC)

Source: Adapted from Roundy et al. (2017)
EC1. Actors actively share knowledge and resources
EC2. Cross-sector partnerships are common in the ecosystem
EC3. Collaboration enhances problem-solving capacity
EC4. Trust among ecosystem actors is high
EC5. Resources flow easily between organizations
EC6. Joint initiatives are frequently launched

Social Innovation Performance (SIP)
Source: Adapted from OECD (2017)
SIP1. Activities address local social challenges
SIP2. Initiatives contribute to SDG-related outcomes
SIP3. Solutions generate measurable social impact
SIP4. We track progress against specific SDG indicators
SIP5. Our work creates systemic social change
SIP6. Impact is sustained beyond project funding

Institutional Support (IS)
Source: Adapted from Stam (2015)
IS1. Government policies support social entrepreneurship
IS2. Funding mechanisms facilitate ecosystem development
IS3. Regulatory frameworks enable social innovation
IS4. Public procurement favors social enterprises

Control Variables
C1. Organization size (number of employees)
C2. Organization age (years since founding)
C3. Country (drop-down selection)
C4. Actor type (drop-down selection)
C5. Primary SDG focus (multiple selection)