Digital Embeddedness and Green Venture Performance: A Network-Based Analysis of Digital Technology Communities in Sustainability Transitions

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Abstract. Digital technologies are widely regarded as enablers of sustainability transitions, yet their adoption among green ventures and its relationship with venture performance remain underexplored. Using data on 6,580 green ventures founded between 2016 and 2025 from Crunchbase, this study develops a network-based taxonomy of digital technologies from keyword co-occurrence. We identify six digital technology communities and develop a Venture Digital Embeddedness Index (VDEI) to capture the breadth and depth of digital engagement, then use multilevel logistic regression models to link digitalization to venture performance. The results show that only 20.6% of ventures are assigned to a technology community, with adoption concentrated in enterprise software and artificial intelligence (AI). Digital community membership raises the odds of early-stage revenue and financing but not of reaching higher-value outcomes, whereas greater digital embeddedness is positively associated with generating both low and high revenues. The associations also diverge by community: ventures in the AI, software, and internet of things communities are more likely to secure early-stage funding, yet AI ventures are less likely to reach higher-value revenue outcomes. By distinguishing technology communities from digital embeddedness, we demonstrate that digital transformation is multidimensional rather than uniform, creating heterogeneous performance pathways

Keywords: Green entrepreneurship, digital technology, digital adoption, digital embeddedness, venture performance, network analysis, multilevel modeling.

1. Introduction

The transition toward environmentally sustainable economic activity has made green entrepreneurship an important mechanism for addressing climate change, resource depletion, and ecological degradation. Green ventures combine environmental objectives with economic value creation by developing sustainability-oriented products, processes, and services and by responding to market failures and environmental needs that conventional firms may overlook (Cohen & Winn, 2007; Shepherd & Patzelt, 2011). As institutional and policy attention to sustainability transitions has grown, so too has scholarly interest in the conditions that shape the emergence, development, and performance of these ventures (Geels, 2020; Köhler et al., 2019).

At the same time, digital technologies have become increasingly central to how new ventures are created, organized, financed, and scaled. Research on digital entrepreneurship shows that these technologies can reduce experimentation costs, enable rapid scaling, and reshape entrepreneurial opportunities by making venture processes more flexible, generative, and less constrained by physical boundaries (Nambisan, 2017; Autio et al., 2018). Digitalization has also transformed entrepreneurial ecosystems by altering how entrepreneurs, investors, customers, and other stakeholders interact. Accordingly, digital technology is increasingly understood not merely as a supporting tool, but as a constitutive element of contemporary entrepreneurial activity (Autio et al., 2018).

Despite the substantial development of both literatures, their intersection remains comparatively underexplored. Research on green ventures has primarily emphasized institutional, financial, and market conditions (Cohen & Winn, 2007; Shepherd & Patzelt, 2011), whereas digital entrepreneurship research has generally evolved without an explicit focus on environmental sustainability (Nambisan, 2017). Even where these literatures intersect, digitalization is often treated as an aggregate or binary characteristic, with ventures classified broadly as digital or non-digital rather than as a heterogeneous set of technology domains that includes artificial intelligence, cloud computing, blockchain, data analytics, robotics, and the Internet of Things (Berger et al., 2018; Yoo et al., 2010). Such aggregation is analytically convenient, but it may obscure the distinct roles that different digital technologies play within ventures and the possibility that they are associated with different performance outcomes.

This distinction matters because digital technologies differ in their architectures, functions, resource requirements, and roles in venture operations. AI systems, for example, typically require different data infrastructures, talent, and capital commitments than IoT or blockchain applications, and these differences plausibly translate into different relationships with commercial and financial outcomes. Treating ventures simply as digitalized or non-digitalized may therefore obscure which technologies matter, as well as the difference between a venture's overall degree of digital engagement and its participation in a particular technology domain.

This study addresses these limitations by examining digital technology adoption and its association with the revenue and funding outcomes of green ventures, using Crunchbase data on 6,580 green ventures founded between 2016 and 2025. It makes three contributions. First, it develops a network-based taxonomy of digital technologies from technology-tag co-occurrences and community detection. Berger et al.'s (2018) multilayer framework, which conceptualizes digital technologies as operating across distinct but interacting layers rather than as a single undifferentiated category, informs the identification and interpretation of relevant technologies, while the resulting communities are derived empirically rather than imposed a priori. Second, the study develops a Venture Digital Embeddedness Index (VDEI) that captures both the breadth and depth of a venture's digital engagement. This provides a more granular alternative to a binary digitalized/non-digitalized distinction and allows variation in the extent of digital engagement to be examined directly. Third, the study uses multilevel logistic regression to examine how aggregate digitalization, the VDEI, and community-specific participation relate to revenue and funding outcomes. The multilevel design accounts for clustering of ventures within entrepreneurial ecosystems, recognizing that outcomes may be shaped jointly by venture-level characteristics and shared ecosystem conditions.

If digital technologies function as constitutive, opportunity-shaping resources rather than interchangeable tools (Autio et al., 2018; Nambisan, 2017), their association with venture outcomes should depend on which technologies are involved and how digital engagement is measured, not merely on whether a venture is digital at all. These premises motivate three research questions:

RQ1: What digital technology communities can be identified among green ventures, and how prevalent are they?
RQ2: How are aggregate digitalization and venture digital embeddedness associated with green venture revenue and funding outcomes?

RQ3: How is participation in specific digital technology communities associated with green venture revenue and funding outcomes?

The findings show that identifiable digital technology adoption remains limited among green ventures and is concentrated primarily in enterprise software, cloud computing, artificial intelligence, and machine learning. More importantly, the associations between digitalization and venture outcomes are not uniform. Aggregate digitalization is associated with higher odds of reporting revenue and funding below USD 1 million, but shows no significant association with outcomes above that threshold. Greater digital embeddedness is positively associated with both revenue indicators, while individual technology communities show distinct patterns across revenue and funding outcomes.

These findings indicate that the relationship between digitalization and green venture performance depends on how digitalization is measured, which technologies are involved, and whether performance is assessed through revenue or external funding. They challenge the assumption that digital technology adoption is uniformly associated with stronger commercial and financial outcomes, and more broadly demonstrate the value of treating digitalization as a heterogeneous, multidimensional venture characteristic rather than a single binary condition.

2. Literature Review

2.1 Green Entrepreneurship and Sustainable Venture Creation

Green entrepreneurship is a distinct stream within the sustainable entrepreneurship literature, conceptualizing entrepreneurial action as contributing to the preservation of nature, life-support systems, and communities while generating economic and non-economic value (Shepherd & Patzelt, 2011). Green ventures combine commercial objectives with efforts to address environmental problems through new products, processes, services, and business models. This literature is grounded partly in the recognition that environmental degradation often results from market imperfections: externalities, information asymmetries, inefficient pricing, and imperfect competition can discourage established firms from addressing environmental problems while simultaneously creating opportunities for entrepreneurs to introduce environmentally beneficial innovations (Cohen & Winn, 2007). Green ventures thus operate at the intersection of opportunity recognition and environmental stewardship.

A complementary eco-innovation literature examines organizational and contextual factors associated with environmentally oriented innovation, commonly identifying regulatory pressure, technological capability, and market demand as key drivers (Horbach et al., 2012). Although this research concerns established firms, its emphasis on the interaction between internal capabilities and external conditions is relevant to ventures, which similarly vary in technological resources, organizational capabilities, market environments, and access to finance — all of which may shape technology orientation and commercial development.

Digital technologies introduce a further source of heterogeneity among green ventures, potentially supporting sustainability-oriented entrepreneurship through environmental data collection, coordination of distributed value chains, resource-efficiency improvements, and new forms of stakeholder engagement. Yet the literature linking digital technologies to sustainable entrepreneurship remains dispersed. Holzmann and Gregori (2023) describe digital sustainable entrepreneurship as a developing field in which digital technologies contribute to environmental and social value creation, venture viability, stakeholder inclusion, and business-model innovation — while noting that considerably more venture-level empirical evidence is needed.

Importantly, the interaction between environmental and digital orientations should not be assumed uniformly beneficial. Ardito et al. (2021) find that digital and environmental orientations are individually associated with stronger innovation outcomes among SMEs, but that pursuing both simultaneously does not automatically yield complementary performance benefits — suggesting ventures may face real strategic and organizational tension in combining the two agendas.

In sum, green entrepreneurship research explains *why* environmental problems generate entrepreneurial opportunity, but offers limited evidence on *which* digital technology configurations are associated with green ventures, and how those configurations relate to commercial and financial outcomes.

2.2 Digital Entrepreneurship and the Heterogeneity of Digital Technologies

Digital entrepreneurship research examines how digital technologies reshape entrepreneurial opportunities, processes, and outcomes. Nambisan (2017) argues that digital technologies lower experimentation costs, enable rapid adaptation and scaling, and introduce new forms of

uncertainty tied to the generative nature of digital artifacts: because digital components can be modified and recombined after their initial introduction, entrepreneurial processes built on them tend to be more flexible, distributed, and harder to predict than processes centered on physical products alone.

Digitalization also reshapes the environments in which entrepreneurial activity occurs. Autio et al. (2018) show that digital affordances reconfigure entrepreneurial ecosystems by affecting where opportunities arise, how resources are mobilized, and how ecosystem participants coordinate. Sussan and Acs (2017) similarly integrate digital and entrepreneurial ecosystem perspectives, showing that digital entrepreneurship depends on interactions among digital infrastructure governance, digital users, entrepreneurs, and digital marketplaces. Digital technology is therefore best understood not as an operational tool but as a potentially constitutive feature of a venture's products, processes, business model, and external relationships.

This constitutive role, however, is not uniform across technologies. Information systems research provides the technical grounding for this heterogeneity: Yoo et al. (2010) identify reprogrammability and layered modular architecture as core properties of digital innovation, with technologies operating across device, network, service, and content layers that allow components to be recombined into new configurations. Building on this, Berger et al. (2018) develop a multilayer taxonomy based on reprogrammability, data homogenization, and self-reference, distinguishing core digital technologies from supporting infrastructures and application-level technologies.

This heterogeneity has direct implications for venture research. Artificial intelligence, cloud computing, data analytics, blockchain, robotics, and IoT differ substantially in technological maturity, implementation cost, infrastructure requirements, and scalability. Cloud computing and enterprise software function as relatively general-purpose infrastructure across industries, while robotics and IoT typically require specialized physical assets and complementary infrastructure; AI and data analytics depend heavily on data availability and analytical capability; blockchain applications face distinct regulatory and legitimacy hurdles. Collapsing these into a single "digital" category obscures this variation and implicitly treats all digital engagement as strategically and economically equivalent — including the difference between a venture linked to one peripheral technology and one whose profile spans several strongly interconnected domains.

This study accordingly distinguishes among aggregate digitalization**,** participation in individual technology communities, and network-based digital embeddedness. Because the underlying data derive from publicly reported Crunchbase tags, embeddedness here should be interpreted as the breadth and structural significance of a venture's *identifiable* technology profile — not as a direct measure of how deeply technologies are operationally integrated into the venture.

2.3 Digitalization and Commercial Venture Outcomes

Digital transformation research suggests that the organizational consequences of digital technology depend on the scope and manner of its use, not on adoption per se. Verhoef et al. (2021) distinguish digitization (converting analog information to digital form), digitalization (using digital technologies to change organizational processes), and digital transformation (broader reconfiguration of structures, strategies, and value-creation processes) — a distinction that cautions against treating digitalization as a single adoption event, since ventures differ in the number and types of technologies involved, their ability to combine them, and how far their business models are actually organized around digital capability.

Empirical work generally finds positive but *conditional* relationships between digitalization and firm performance. Eller et al. (2020) find that IT, employee skills, and digital strategy are associated with digitalization, and that digitalization in turn relates positively to SME financial performance — but that possessing a digital strategy or digital skills alone is insufficient; performance depends on how these resources are jointly configured. Kim and Jin (2024) similarly find digital capabilities positively associated with SME entrepreneurial performance, with opportunity capability as a key mediating mechanism and entrepreneurial leadership as a conditioning factor — indicating that digital technology creates value partly through the organizational capacity to identify and exploit opportunities, not through adoption alone. Merín-Rodrigáñez et al. (2024) add that business-model innovation partially mediates the relationship between digital transformation and SME performance, suggesting digital investment yields limited commercial return unless translated into changes in the venture's value proposition or revenue model.

These findings cannot be transferred to green ventures uncritically. Green ventures often face long development periods, high research and infrastructure requirements, regulatory uncertainty, and difficulty converting environmental value into customer willingness to pay. Digital capabilities could help offset some of these constraints, but could equally add

organizational complexity and resource burden. The relationship between digitalization and revenue therefore likely depends on the specific technology, the venture's complementary capabilities, and its ability to convert digital resources into marketable output.

Revenue itself captures realized commercial activity and market acceptance, though not profitability, growth, or survival. Distinguishing ventures reporting revenue below versus above USD 1 million nonetheless allows different measures of digital orientation to be linked to distinct, observable categories of commercial activity.

2.4 Digitalization and External Funding

External funding is a conceptually distinct outcome from revenue: revenue reflects transactions between ventures and customers, while funding reflects investor assessments of future potential, risk, legitimacy, and expected return. A technology may therefore relate positively to one without relating positively to the other.

Information asymmetry is especially acute in new-venture financing, where investors have limited direct evidence of venture quality. Ventures address this partly through observable signals — founder experience, patents, partnerships, accelerator participation, technology orientation — whose effectiveness, per Colombo's (2021) review, depends on the sender, the signal itself, investor type, and the broader financing environment.

A venture's association with digital technologies plausibly functions as one such signal: AI, data analytics, and cloud computing may signal innovativeness, scalability, or participation in a growing market. But this signal value is unlikely to be uniform — investor response depends on technical expertise, market familiarity, risk tolerance, and assessment of commercialization potential. Technology-intensive ventures also often require substantial external resources (data and compute costs for AI, physical equipment for robotics, hardware and connectivity for IoT), which can simultaneously raise capital needs *and* technical/commercialization risk. A digital technology profile may thus signal growth potential and elevated uncertainty at once.

Green ventures' environmental orientation adds a further layer. Hossnofsky et al. (2025) find environmental orientation positively associated with pre-IPO funding in early- and later-stage rounds — particularly with prominent VC investors — but not in seed-stage funding, underscoring that signal effectiveness is sensitive to venture maturity and investor context.

Digital and environmental signals may interact in similarly complex ways: investors might read the combination as evidence a venture can deploy scalable technology against environmental problems, or instead as a marker of compounded technological and capital-intensity risk. The funding implications of green-venture digitalization therefore cannot be inferred directly from its relationship with commercial outcomes, which is why this study distinguishes funding below and above USD 1 million as empirically observed thresholds rather than theoretically universal financing stages.

2.5 Entrepreneurial Ecosystems and Contextual Variation

Venture development does not occur independently of geographic and institutional context. Entrepreneurial ecosystems comprise interconnected entrepreneurs, investors, institutions, networks, support organizations, and cultural and material resources that jointly shape entrepreneurial activity and performance (Stam, 2015; Spigel, 2017). The value of any given resource depends partly on this surrounding context — access to skilled labor, research institutions, digital infrastructure, and finance varies by location, as do the relationships among these resources; an ecosystem can possess universities and investors without the intermediary networks needed to connect them productively (Spigel, 2017).

These contextual differences matter particularly for digital and green ventures alike: digital entrepreneurship depends on technological infrastructure, digital skills, and regulatory arrangements (Sussan & Acs, 2017), while green entrepreneurship depends on environmental policy, public procurement, impact-investment networks, and access to scientific and engineering expertise. Ventures sharing a geographic context may therefore share conditions that shape both their technology profiles and their revenue and funding outcomes — which is analytically important, since treating ventures as fully independent risks underestimating this shared contextual influence. A multilevel approach addresses this by estimating venture-level associations while accounting for clustering within the geographic grouping used in the analysis.

One clarification is warranted: where the models group ventures by country, the resulting estimates capture country-level contextual variation, not a direct measure of the full relational and institutional structure implied by "entrepreneurial ecosystem" in the strict sense.

2.6 Synthesis and Research Gap

Three gaps emerge from this literature. First, limited evidence exists on which digital technology *configurations* — as opposed to individual technologies considered in isolation — are associated with green ventures; approaches that assign technologies to predetermined categories may miss the relationships among technologies that co-occur within venture profiles. Second, aggregate and binary digitalization measures conceal variation in the types, breadth, and network position of a venture's technology engagement; distinguishing aggregate digitalization, network-based embeddedness, and technology-community participation offers a more differentiated view. Third, the relationships among digitalization, revenue, and external funding remain insufficiently disentangled for green ventures specifically — since commercial activity and investor allocation decisions arise through different processes (Colombo, 2021; Hossnofsky et al., 2025), a given form of digital engagement may relate differently to each, and these relationships may further vary across the below-/above-USD 1 million categories observed in the data.

Addressing these gaps requires an approach that treats technology heterogeneity, differentiated measures of digital orientation, separated commercial and funding outcomes, and shared contextual conditions as jointly necessary rather than optional refinements. This study combines an empirically derived network-based technology taxonomy, a Venture Digital Embeddedness Index, and multilevel logistic regression to provide exactly that.

3. Data and Methodology

This study draws on data on green ventures from Crunchbase (https://www.crunchbase.com/), a widely used database of technology startups and entrepreneurial ventures. Crunchbase provides firm-level information on business activities, location, founding date, employment, and financing history, aggregated from venture capital firms, incubators, accelerators, entrepreneurs, and publicly available sources, with data quality supported by automated verification processes including AI, machine-learning algorithms, and web-crawling technologies. Since its founding in 2007, Crunchbase has been used as a data source in entrepreneurship and innovation research (Dalle et al., 2017).

The sample is limited to ventures founded between 2016 and 2025 and classified by Crunchbase under "Green Tech," "Clean Tech," or "Sustainability." This window was chosen to capture entrepreneurial activity following the Paris Agreement, which entered into force in late 2016 and strengthened the institutional framework for sustainability transitions and climate-oriented innovation (Köhler et al., 2019; Geels, [year to confirm]). After applying these criteria and removing ventures with missing values on [specify: e.g., founding date, industry classification, or country], the final dataset comprises 6,580 green ventures. Table 1 reports their distribution across founding-year cohorts.

Table 1. Number of green ventures in the period 2016-2025

Time period	Number of green ventures
2016	758
2017	785
2018	914
2019	604
2020	1015
2021	995
2022	594
2023	486
2024	305
2025	124

Source: CrunchBase.

Indusrtry and Technology keyword Classification

To identify digital technologies embedded within green ventures, we analyze the business and technology keywords Crunchbase assigns to each venture, which capture industry focus, operational domain, and technological orientation at a granular, venture level. Table A1 (Annex I) reports the full frequency distribution of these keywords. The most common—Renewable Energy (n = 754), Energy (n = 749), Manufacturing (n = 669), and Software (n = 655)—reflect the sector's overall composition, while keywords such as Artificial Intelligence (n = 334), Analytics (n = 97), Mobile Apps (n = 81), Hardware (n = 73), and E-Commerce Platforms (n = 40) capture the digital technology dimension central to this analysis. This distribution forms the basis for the keyword co-occurrence network analysis that follows, in which relationships among digital technology keywords and broader business/industry terms are modeled to identify clusters of thematically and technologically related ventures.

Classification of Digital Technologies — Theoretical Framework

To classify digital-technology keywords, we draw on Berger et al.'s (2018) multi-layer taxonomy, which characterizes digital artifacts by three properties: re-programmability, data homogenization, and self-referential capacity for generating and processing digital information. We complement this with the Layered Modular Architecture perspective (Yoo et al., 2010), which situates digital innovation across device, network, service, and content layers, and with Cyber-Physical Systems theory to justify including technologies spanning computation and physical action.

Using these frameworks, we manually classify all digital-technology-relevant keywords into three tiers: (1) Core Digital Technologies (pure digital artifacts), (2) Digital Infrastructure and Enabling Technologies, and (3) Applications and Practices of Digital Technologies. This structure separates digital technologies in the strict, artifact-based sense from the infrastructure that supports them and the downstream products in which they are embedded — preventing conflation of technology adoption with technology-enabled output.

Core Digital Technologies (Table A4). This tier comprises 33 keywords satisfying Berger et al.'s (2018) criteria of re-programmability, homogenized data, and self-referential computation. It spans software (Software, Consumer Software, Enterprise Software); computational intelligence (AI, Machine Learning, and subdomains including Generative AI, NLP, Computer Vision); data engineering (Database, Data Management, Data Integration, Data Mining, Big Data); cloud architectures (Cloud Computing, Cloud Infrastructure, SaaS, PaaS); cybersecurity; geospatial and remote sensing; distributed ledger technologies (Blockchain, Web3); automation (RPA, Robotics); connectivity (IoT, Sensors); and immersive/3D computation (Virtual Reality, 3D Technology).

Two inclusions warrant justification. Sensors and Remote Sensing are retained here rather than treated as infrastructure, since environmental innovation research treats sensing technologies as active digital data-acquisition systems central to smart irrigation, air quality monitoring, precision agriculture, and biodiversity tracking [citation needed], not as passive hardware. Blockchain and Web3 are classified as core technologies because their defining function — decentralized validation, storage, and execution of digital transactions — satisfies Berger et al.'s self-referential and data-homogenization criteria, despite depending on distributed network infrastructure.

Digital Infrastructure and Enabling Technologies (Table A5). This tier comprises the physical and architectural substrate that enables digital computation without itself constituting a digital artifact: hardware (Hardware, Electronics, Semiconductors), physical infrastructure (Data Centers, IT Infrastructure), and communication infrastructure (Telecommunications, Satellite Communication, Communications Infrastructure). Following Yoo et al. (2010), these occupy the device and network layers underlying the service- and content-layer artifacts in Table A4. We classify Information Technology and ICT as foundational rather than specific technologies and exclude both from the dictionary, following the OECD's (2017) distinction between specific technologies and broad sector categories: these umbrella terms carry little signal about which underlying technologies are actually present, and including them risks inflating measured adoption.

Applications and Practices of Digital Technologies (Table A6). This tier comprises keywords representing capabilities, practices, or application domains rather than technologies themselves. Software Engineering is a development practice, not an artifact. Industrial Automation is excluded as overly broad, conflating software, control systems, and machinery without specifying the underlying technology. Autonomous Vehicles and Drones are application platforms embedding digital technologies (AI, sensors, robotics) rather than technologies in themselves, and Cryptocurrency, NFTs, and DeFi are similarly classified as blockchain applications — business models and assets built atop blockchain infrastructure — rather than core technologies.

Our final dictionary comprises the 33 keywords in Table A4. Keywords in Tables A5 and A6 are excluded, since their presence reflects supporting infrastructure, overly broad categorization, or downstream application rather than direct technology adoption. This tiered exclusion ensures the adoption measure captures genuine engagement with programmable, data-driven artifacts rather than incidental association with hardware, infrastructure, or technology-enabled products.

Identification of Digital Technology Communities

To identify meaningful groups of digital technologies, we extracted all Core Digital Technology keywords (Table A4) associated with ventures in the dataset, excluding broader industrial or application-sector keywords so the analysis focused exclusively on digital artifacts rather than industry domains.

We then constructed a technology co-occurrence network based on the simultaneous appearance of digital technology keywords within individual venture profiles, on the assumption that co-occurring technologies are more likely to represent related capabilities or complementary knowledge domains. We compared four graph specifications differing in co-occurrence strength and frequency thresholds (Table A7), evaluating both raw co-occurrence counts and normalized pointwise mutual information (NPMI), which adjusts for keyword frequency to capture association strength independent of how common individual technologies are.

Network quality was assessed using modularity (Q), which measures how cleanly a network partitions into internally cohesive, externally distinct communities. The network built on positive NPMI values with a minimum co-occurrence frequency of three (Variant D) achieved the highest modularity (Q = 0.6003), indicating the clearest community structure, and was selected for subsequent analysis.

Community detection on this network identified six digital technology communities (Table 2): (1) AI and Machine Learning, (2) Robotics and 3D Technologies, (3) Enterprise Software and Cloud Computing, (4) Data and Analytics, (5) Blockchain and Web3, and (6) IoT and Sensor Systems — clusters of technologies that frequently co-occur within ventures, representing broader technological capability domains rather than isolated technologies.

Table 2. Technology Communities Identified Through Network Analysis

Community Number	Community Name	Digital Technology Tag (Frequency)	Community Frequency
Community 0	AI & Machine Learning	Artificial Intelligence (AI) (242), Machine Learning (113), Generative AI (16), Computer Vision (13), Data Collection and Labeling (7), Remote Sensing (5)	396
Community 1	Robotics & 3D Tech	Robotics (35), 3D Technology (11), Robotic Process Automation (RPA) (5)	51
Community 2	Enterprise Software & Cloud Computing	Software (330), SaaS (182), Enterprise Software (49), Cloud Computing (18), PaaS (8), Consumer Software (8), Cloud Management (7), Cloud Infrastructure (6), Mapping Services (4), Developer Platform (4)	616
Community 3	Data & Analytics	Analytics (60), Big Data (47), Predictive Analytics (24), Data Visualization (22), Business Intelligence (18), Geospatial (15), Database (13), Data Integration (10)	209
Community 4	Blockchain & Web3	Blockchain (67), Web3 (24), Data Mining (5)	96
Community 5	IoT & Sensor Systems	Internet of Things (82), Sensor (15), Cloud Data Services (7)	104

Note. *Communities were identified using the NPMI > 0 and co-occurrence frequency ≥ 3 network variant (Q = 0.589). Community frequency represents the cumulative occurrence count of technologies assigned to each community, while* n *denotes the number of technology tags within the community.*

Assignment of Ventures to Technology Communities

After establishing the community structure, we assigned individual ventures to communities using a multi-method procedure, since many ventures carried multiple technology keywords and some lacked any keyword represented in the network. First, a direct overlap approach assigned ventures based on which community their keywords belonged to. Second, an NPMI-based method incorporated the strength of associations from the co-occurrence network. Third, a Naive Bayes classifier was trained on the subset of ventures with at least one matched keyword (n = 1,356) and applied to the full sample of 6,580 ventures to predict the most likely community membership.

To assess reliability, we calculated pairwise agreement across the three methods (Table A8). Agreement was highest between the overlap and Naive Bayes approaches (98.3%), and around 79% between the NPMI-based method and each of the others. Overall, 1,068 ventures received consistent assignments across all three methods, while only four ventures (0.1% of the matched subsample) were ambiguously classified.

The final classification shows Enterprise Software and Cloud Computing as the largest community (666 ventures), followed by AI and Machine Learning (354 ventures), with Blockchain and Web3, IoT and Sensor Systems, Data and Analytics, and Robotics and 3D Technologies forming smaller but distinct segments (Table 3). A substantial share of ventures (79.4%) remained unassigned, lacking any keyword represented in the final co-occurrence network.

Table 3. Community assignment results

Community	Description	Ventures	% of Total
Community 0	AI & Machine Learning	354	5.4%
Community 1	Robotics & 3D Tech	50	0.8%
Community 2	Enterprise Software & Cloud Computing	666	10.1%
Community 3	Data & Analytics	106	1.6%
Community 4	Blockchain & Web3	98	1.5%
Community 5	IoT & Sensor Systems	82	1.2%
Unassigned	No matching graph tags	5,224	79.4%
Total		6,580	100.0%

Validation of Community Structure

To evaluate whether the identified communities represented distinct technological domains rather than overlapping categories, we conducted a community pair analysis (Table A9) using three complementary measures: the phi coefficient (φ), capturing correlation between venture memberships across communities; the Jaccard coefficient, measuring shared ventures relative to combined community membership; and inter-community NPMI, capturing the average strength of cross-community technology associations.

Overlap between communities was generally low. Moderate co-adoption appeared between AI & Machine Learning and Enterprise Software & Cloud Computing (φ = 0.223), and between AI & Machine Learning and Data & Analytics (φ = 0.174), but no pair exceeded the predefined merging thresholds (φ > 0.30 and Jaccard > 0.20) on both measures simultaneously. All six communities were therefore retained as analytically distinct.

Together, the community detection, classification, and validation procedures yield a data-driven taxonomy capturing the major digital technology domains represented among green ventures.

Venture Digital Embeddedness Index (VDEI)

To measure the extent to which green ventures embed digital technologies in their business models, we construct a Venture Digital Embeddedness Index (VDEI) based on the validated tag co-occurrence taxonomy from the Louvain community-detection procedure (Variant D: NPMI > 0, edge count ≥ 3, Q = [X]). Rather than imposing categories a priori, the index uses the six empirically identified communities — AI & ML, Software & Cloud, Robotics & RPA, Data & Analytics, Blockchain & Web3, and IoT & Sensors — as its taxonomic foundation, ensuring conceptual and methodological consistency between the network analysis and the index construction.

For each venture i, we parse the raw industry-keyword field into discrete keywords and intersect this set with the keyword dictionary for each digital technology community, yielding a community-specific keyword count. Summing these counts across the six communities produces the venture's total digital tag count, n_i, which underlies both VDEI components.

Breadth (B) measures the proportion of communities in which a venture is active:

$$B_i = \frac{|\{c \in C: n_{i,c} > 0\}|}{|C|},$$

where $n_{i,c}$ is venture *i*'s keyword count in digital technology community *c*, and |C| is the total number of digital technology communities. Consequently, $B_i \in [0,1]$, with larger values indicating broader participation across digital technology communities.

Depth (D) captures the intensity of digital technology engagement, measured as the venture's digital keyword count normalized by the sample maximum:

$$D_i = \frac{n_i}{\max_j(n_j)}$$

This min–max normalization (with an implicit lower bound of zero) rescales depth onto a [0, 1] range comparable to breadth while preserving ventures' relative ordering by digital keyword volume.

The composite index is then calculated as the unweighted mean of the two components:

$$\text{VDEI}_i = \frac{B_i + D_i}{2}$$

We adopt equal weighting a priori rather than a data-driven scheme, since breadth and depth are conceptually complementary rather than substitutable, and an unweighted average avoids arbitrary, sample-specific assumptions at this stage. VDEI is bounded on [0,1] by construction: 0 indicates no detectable digital technology tags (non-digitalized), while values approaching 1 indicate ventures broadly and intensively embedded across the digital technology taxonomy.

Empirical Strategy

To examine whether digital technology adoption contributes to green venture success, we estimate a series of multilevel logistic regression models, testing both the overall effect of digitalization and the differential effects of specific technology domains. Venture success is measured using four binary outcomes: revenue below and above USD 1 million, and funding below and above USD 1 million.

A multilevel framework is necessary because ventures are nested within entrepreneurial ecosystems that differ in institutional environment, resource availability, knowledge infrastructure, and support mechanisms, so outcomes for ventures within the same ecosystem may be correlated, violating the independence assumption of conventional regression. Multilevel logistic regression addresses this nested structure — ventures (Level 1) within ecosystems (Level 2) — by allowing outcomes to vary across ecosystems while estimating venture-level effects (Raudenbush & Bryk, 2002; Hox, 2010; Snijders & Bosker, 2012); ignoring this clustering would risk underestimating standard errors (Gelman & Hill, 2007).

The baseline model tests whether digitalization influences venture success, measured as a binary indicator equal to one if a venture belongs to at least one digital technology community identified through the network-based classification, and zero otherwise. A second set of models, restricted to digitalized ventures, examines the effects of individual communities — AI & ML, Software & Cloud, Robotics & RPA, Data & Analytics, Blockchain & Web3, and IoT & Sensors — alongside VDEI, which captures how broadly and intensively a venture engages with digital domains.

Table 4. Descriptive statistics.

Variables	Variable definition	Obs.	Mean	Std. dev.	Min.	Max.
Revenue_Less_1M	Binary: A value of 1 is assigned if a venture generated revenue Less than $1 million; otherwise, the value is 0.	4477	0.169	0.374	0	1
Revenue_More_1M	Binary: A value of 1 is assigned if a venture generated revenue more than $1 million; otherwise, the value is 0.	5825	0.361	0.480	0	1
Funding_Less_1M	Binary: A value of 1 is assigned if a venture obtained funding Less than $1 million; otherwise, the value is 0.	5296	0.192	0.394	0	1
Funding_More_1M	Binary: A value of 1 is assigned if a venture obtained funding more than $1 million; otherwise, the value is 0.	5564	0.231	0.421	0	1
Size	Number of employees	6580	1.578	1.045	0	9
Age	Time since the venture has been founded (in months)	6580	74.413	29.546	0	120
Number of founders	Number of founders of the venture	6580	0.886	1.130	0	7
Digitalized	Binary: If the venture belongs to digital technology community	6580	0.206	0.405	0	1
Seed funding	Funding stage: Seed funding	6580	0.287	0.452	0	1
Early-stage venture	Funding stage: Early-stage venture	6580	0.043	0.203	0	1
M&A	Funding stage: M&A	6580	0.018	0.134	0	1
IPO	Funding stage: IPO	6580	0.009	0.093	0	1
Late-stage venture	Funding stage: Late-stage venture	6580	0.005	0.070	0	1
Private equity	Funding stage: Private equity	6580	0.004	0.065	0	1

AI & ML	Binary variable equal to 1 if the venture is associated with technologies belonging to the AI & Machine Learning community; 0 otherwise.	1356	0.281	0.450	0	1
Software & Cloud	Binary variable equal to 1 if the venture is associated with the Enterprise Software & Cloud Computing community; 0 otherwise	1356	0.618	0.486	0	1
Robotics & RPA	Binary variable equal to 1 if the venture is associated with the Robotics community; 0 otherwise.	1356	0.063	0.242	0	1
Data & Analytics	Binary variable equal to 1 if the venture is associated with the Data & Analytics community, including analytics; 0 otherwise.	1356	0.163	0.369	0	1
Blockchain & Web3	Binary variable equal to 1 if the venture is associated with the Blockchain & Web3 community; 0 otherwise.	1356	0.109	0.312	0	1
IoT & Sensors	Binary variable equal to 1 if the venture is associated with the IoT & Sensor Systems community; 0 otherwise.	1356	0.114	0.318	0	1
VDEI	Venture Digital Embeddedness Index (VDEI)	1356	0.231	0.116	0.155	0.833

Source: Developed by authors, based on CrunchBase.

All models include a common set of controls: venture size (Crunchbase employee-size categories), age (months since founding), and number of founders (team size and founding resources). Funding-stage indicators — seed, early-stage venture, M&A, IPO, late-stage venture, and private equity — account for differences in development trajectory and financing maturity.

Table 4 reports descriptive statistics. Roughly 20.6% of ventures are classified as digitalized, indicating that most green ventures do not explicitly adopt core digital technologies. Among these, Enterprise Software & Cloud Computing is the most prevalent community (61.8%), followed by AI & Machine Learning (28.1%); about 28.2% combine technologies from multiple communities, suggesting substantial technological diversification. The average venture is roughly 74 months old and employs between one and ten people, reflecting the predominance of early-stage ventures in the sample.

Table 5. Pearson Correlation Matrix.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Employee Count	1.000	0.189	0.033	-0.043	-0.127	0.141	0.080	0.108	0.179	0.082
(2) Age	0.189	1.000	-0.036	-0.157	-0.211	0.052	0.043	0.032	0.056	0.025
(3) Number of Founders	0.033	-0.036	1.000	0.235	0.245	0.152	0.042	0.004	0.061	-0.018
(4) Digitalized	-0.043	-0.157	0.235	1.000	0.139	0.038	0.034	-0.040	0.002	-0.022
(5) Seed funding	-0.127	-0.211	0.245	0.139	1.000	-0.135	-0.086	-0.060	-0.044	-0.041
(6) Early-stage venture	0.141	0.052	0.152	0.038	-0.135	1.000	-0.029	-0.020	-0.015	-0.014
(7) M&A	0.080	0.043	0.042	0.034	-0.086	-0.029	1.000	-0.013	-0.010	-0.009
(8) IPO	0.108	0.032	0.004	-0.040	-0.060	-0.020	-0.013	1.000	-0.007	-0.006
(9) Late-stage venture	0.179	0.056	0.061	0.002	-0.044	-0.015	-0.010	-0.007	1.000	-0.005
(10) Private equity	0.082	0.025	-0.018	-0.022	-0.041	-0.014	-0.009	-0.006	-0.005	1.000

Table 5 reports Pearson correlations among the independent variables. Correlations are generally low, with the largest between number of founders and seed funding ($r = 0.245$). None exceed common multicollinearity thresholds, indicating the explanatory variables capture distinct dimensions of venture characteristics and financing conditions; all variables are retained in the regression analysis.

4. Results and Discussion

Network analysis of digital-technology tag co-occurrences identified six communities under the optimal specification (NPMI > 0; co-occurrence frequency ≥ 3; $Q = 0.589$). Tables 2 and 3 report their composition and venture distribution, respectively. Enterprise Software & Cloud Computing was the largest community, with 616 tag occurrences and 666 ventures (10.1% of the sample), dominated by Software, SaaS, enterprise software, and cloud-computing technologies. AI & Machine Learning was the second largest, comprising 396 tag occurrences and 354 ventures (5.4%). The remaining communities were substantially smaller: Data & Analytics included 209 occurrences and 106 ventures (1.6%); IoT & Sensor Systems, 104 occurrences and 82 ventures (1.2%); Blockchain & Web3, 96 occurrences and 98 ventures (1.5%); and Robotics & 3D Tech, 51 occurrences and 50 ventures (0.8%).

Overall, 5,224 ventures (79.4%) were not assigned to a digital-technology community, leaving 1,356 ventures (20.6%) with identifiable adoption of core digital technologies. Enterprise Software & Cloud Computing and AI & Machine Learning accounted for approximately three-quarters of community assignments, suggesting that digitalization in green entrepreneurship is concentrated in software- and AI-based capabilities rather than specialized technologies such as blockchain, robotics, and IoT.

Digitalization and Venture Performance: Revenue and Funding Outcomes

Table 6 reports four multilevel logistic regression models examining digitalization's association with green ventures' probability of falling into each revenue and funding category. Digitalization is positively and significantly associated with the odds of reporting revenue below USD 1 million and funding below USD 1 million, but shows no significant association

with revenue or funding above USD 1 million. This pattern suggests digitalization is linked to ventures' presence in the lower revenue and funding tiers rather than to reaching higher performance thresholds — a result that runs counter to the common assumption that digital technology adoption straightforwardly drives venture growth, and warrants discussion in light of the earlier finding that most green ventures remain non-digitalized.

Venture age shows opposite associations across outcome types: positively associated with both revenue outcomes but negatively associated with both funding outcomes, indicating that older ventures are more likely to generate revenue at either level but less likely to secure funding at either level. Founder count is positively associated with all four outcomes, most strongly for the higher funding tier, consistent with larger founding teams signaling stronger fundraising capacity.

Venture size shows a consistent pattern across both revenue and funding outcomes: negatively associated with the lower tier but positively associated with the higher tier, suggesting that larger ventures are underrepresented among the smallest revenue and funding categories but overrepresented among the largest.

Table 6. Estimation results for green ventures by revenue and funding levels (above and below USD 1 Million)

Variable	Revenue_Less_1M	Revenue_More_1M	Funding_Less_1M	Funding_More_1M
	(1)	(2)	(3)	(4)
Intercept	-4.070*** (0.042)	-3.658*** (0.031)	-1.076*** (0.037)	-2.740*** (0.036)
Size	-0.059** (0.026)	0.552*** (0.016)	-0.331*** (0.025)	0.424*** (0.017)
Age	0.025*** (0.001)	0.026*** (0.000)	-0.007*** (0.001)	-0.003*** (0.000)
Number of founders	0.341*** (0.026)	0.227*** (0.022)	0.540*** (0.025)	0.852*** (0.023)
Digitalized	0.499*** (0.081)	-0.130 (0.073)	0.233*** (0.073)	-0.001 (0.076)
Seed funding	0.599*** (0.068)	-0.079 (0.061)		
Early-stage venture	-0.165 (0.264)	0.652*** (0.141)		
M&A	0.096 (0.302)	-0.256 (0.224)		
IPO	1.235*** (0.430)	0.519 (0.348)		
Late-stage venture	-1.716 (1.305)	0.003 (0.466)		
Private equity	-2.107* (1.186)	-0.491 (0.444)		

Random intercepts at the city level	0.360	0.488	0.425	0.561
Obs.	4477	5825	5296	5564

Significance level: '***' 0.01, '**' 0.05.

Among funding-stage controls (revenue models only), IPO status is associated with substantially higher odds of the lower revenue outcome, while private equity involvement is associated with lower odds; neither reaches significance in the higher revenue model. Early-stage venture funding is positively associated with the higher revenue outcome but not the lower one.

Table 7. Classification performance metrics for model (1) – green ventures with revenues above USD 1 million

	Precision	Recall	F1-score	Support
0.0	0.84	0.99	0.91	3722
1.0	0.67	0.08	0.14	755
Accuracy			0.84	4477
Macro avg.	0.76	0.54	0.53	4477
Weighted avg.	0.81	0.84	0.78	4477

ROC-AUC: 0.719

Table 8. Classification performance metrics for model (2) – green ventures with revenues below USD 1 million

	Precision	Recall	F1-score	Support
0.0	0.73	0.86	0.79	3722
1.0	0.64	0.44	0.52	2103
Accuracy			0.71	5825
Macro avg.	0.69	0.65	0.66	5825
Weighted avg.	0.70	0.71	0.69	5825

ROC-AUC: 0.767

Table 9. Classification performance metrics for model (3) – green ventures with funding below USD 1 million

	Precision	Recall	F1-score	Support
0.0	0.82	0.98	0.89	4280
1.0	0.46	0.06	0.11	1016
Accuracy			0.81	5296
Macro avg.	0.64	0.52	0.50	5296
Weighted avg.	0.75	0.81	0.74	5296

ROC-AUC: 0.709

Table 10. Classification performance metrics for model (4) – green ventures with funding above USD 1 million

	Precision	Recall	F1-score	Support
0.0	0.81	0.95	0.87	4280
1.0	0.61	0.25	0.36	1284

Accuracy			0.79	5564
Macro avg.	0.71	0.60	0.62	5564
Weighted avg.	0.76	0.79	0.75	5564

ROC-AUC: 0.776

Tables 7–10 report classification performance for the four multilevel logistic regression models. ROC-AUC values range from 0.709 to 0.776, indicating modest-to-moderate discriminative ability across all models — well above chance (0.5), though below what would be considered strong classification performance.

Performance is uneven across classes, reflecting substantial class imbalance in three of the four outcomes. Models 1 (revenue below USD 1 million) and 3 (funding below USD 1 million) show markedly poor minority-class recall (0.08 and 0.06, respectively): despite reasonable overall accuracy (0.84 and 0.81), these models correctly identify only a small fraction of ventures in the minority category. This gap between high accuracy and low minority-class recall is a classic signature of class imbalance — both models default toward predicting the majority class, inflating aggregate performance metrics while offering limited discriminative value for the outcome of substantive interest.

Models 2 (revenue above USD 1 million) and 4 (funding above USD 1 million) perform more evenly, reflecting less extreme class imbalance (support ratios of roughly 1.8:1 and 3.3:1, compared with 4.9:1 and 4.2:1 for Models 1 and 3) and correspondingly higher minority-class recall (0.44 and 0.25) and F1-scores (0.52 and 0.36). Model 2 achieves the best balance between precision and recall for the minority class, alongside the second-highest ROC-AUC (0.767).

Taken together, the four models show acceptable discrimination but limited sensitivity to minority-class outcomes — a pattern driven by class imbalance rather than model misspecification. Given this imbalance, we interpret the regression coefficients in Table 6 primarily as indicators of association rather than as evidence of strong predictive accuracy. Future extensions could apply class weighting, resampling, or precision-recall–optimized thresholds to improve minority-class detection.

Digital Embeddedness and Technology-Specific Effects on Venture Performance

Table 11 restricts the sample to digitalized ventures and examines how individual technology communities and digital embeddedness (VDEI) relate to revenue and funding outcomes. VDEI is the most consistently significant digital variable in the table, though its direction varies by

outcome type. It is strongly positive for both revenue outcomes, indicating that ventures with broader and more intensive digital technology engagement are substantially more likely to fall into either revenue category relative to non-digitalized ventures in the base group. For funding, by contrast, VDEI is significantly negative for the lower tier and not significant for the higher tier — suggesting digital embeddedness is more closely tied to revenue generation than to attracting external funding, and that highly embedded digital ventures are specifically underrepresented among those with modest funding levels.

Effects among individual technology communities are sparse but not uniform. AI & ML shows a notable sign split — negatively associated with the higher revenue outcome but positively associated with the lower funding outcome — suggesting these ventures may attract smaller-scale funding more readily than they convert that investment into higher revenue. Software & Cloud and IoT & Sensors show a similar pattern, each positively associated with the lower funding outcome only. Data & Analytics and Blockchain & Web3, by contrast, are the only communities negatively associated with the higher funding outcome, indicating ventures in these communities are less likely to secure funding above USD 1 million relative to the base group. Robotics & RPA shows no significant association with any outcome, though its wide standard errors (0.308–0.328) likely reflect its small community size (n = 50 ventures; Table 3).

Table 11. Estimation results for digitalized green ventures by revenue and funding levels (above and below USD 1 Million)

Variable	Revenue_Less_1M	Revenue_More_1M	Funding_Less_1M	Funding_More_1M
	(5)	(6)	(7)	(8)
Intercept	-3.983*** (0.083)	-4.760*** (0.076)	-1.937*** (0.074)	-3.907*** (0.080)
Size	-0.161*** (0.054)	0.542*** (0.042)	-0.139*** (0.052)	0.987*** (0.043)
Age	0.031*** (0.001)	0.033*** (0.001)	0.000 (0.001)	0.003*** (0.001)
Number of founders	0.313*** (0.043)	0.246*** (0.040)	0.556*** (0.041)	0.808*** (0.041)
AI & ML	0.037 (0.158)	-0.305** (0.151)	0.614*** (0.136)	0.142 (0.147)
Software & Cloud	-0.043 (0.107)	0.036 (0.095)	0.432*** (0.093)	-0.120 (0.100)
Robotics & RPA	-0.148 (0.319)	-0.270 (0.312)	0.177 (0.308)	-0.237 (0.328)
Data & Analytics	0.258 (0.199)	0.273 (0.178)	0.266 (0.181)	-0.553*** (0.203)
Blockchain & Web3	-0.022 (0.254)	0.032 (0.225)	0.178 (0.218)	-0.600** (0.252)

IoT & Sensors	-0.093 (0.227)	-0.244 (0.222)	0.448** (0.219)	0.301 (0.224)
VDEI	1.269*** (0.315)	1.419*** (0.288)	-0.764*** (0.278)	0.569 (0.302)
Seed funding	0.254** (0.125)	0.323*** (0.116)		
Early-stage venture	-0.101 (0.460)	0.907*** (0.297)		
M&A	-0.229 (0.505)	0.185 (0.404)		
IPO	—	1.504 (1.450)		
Late-stage venture	-0.931 (1.643)	0.666 (0.985)		
Private equity	-0.416 (1.775)	0.304 (1.408)		
Random intercepts at the city level	0.476	0.270	0.574	0.437
Obs.	1009	1128	1030	1064

Significance level: '***' 0.01, '**' 0.05

Classification Performance for Digitalized Ventures

Tables 12–15 report classification performance for the four models restricted to digitalized ventures (Table 11). ROC-AUC values range from 0.687 to 0.821 — notably higher on average than the full-sample models in Tables 7–10 (0.709–0.776), suggesting the technology-community and VDEI predictors add discriminative power beyond the baseline controls.

As before, revenue outcomes classify better than funding outcomes, and higher-tier outcomes better than lower-tier ones. Model 6 (revenue above USD 1M) and Model 8 (funding above USD 1M) perform best, with the strongest minority-class recall (0.48 and 0.44) and highest ROC-AUC (0.816 and 0.821). Model 7 (funding below USD 1M) is weakest, with minority-class recall of just 0.13 and an F1-score of 0.21 — echoing the even lower recall (0.06) for the same outcome in the full sample (Table 9), and suggesting ventures with modest funding are consistently the hardest to classify regardless of specification.

Restricting to digitalized ventures improves ROC-AUC in three of four cases (revenue below: 0.719 → 0.744; revenue above: 0.767 → 0.816; funding above: 0.776 → 0.821). Model 7 is the exception: its ROC-AUC (0.687) is actually lower than its full-sample counterpart (0.709), the one case where adding technology and VDEI predictors does not improve discrimination.

Table 12. Classification performance metrics for model (5) – Digitalized green ventures with revenues below USD 1 million

	Precision	**Recall**	**F1-score**	**Support**

0.0	0.82	0.97	0.89	781
1.0	0.73	0.27	0.39	228
Accuracy			0.81	1009
Macro avg.	0.77	0.62	0.64	1009
Weighted avg.	0.80	0.81	0.78	1009

ROC-AUC: 0.744

Table 13. Classification performance metrics for model (6) – Digitalized green ventures with revenues above USD 1 million

	Precision	**Recall**	**F1-score**	**Support**
0.0	0.80	0.91	0.85	781
1.0	0.70	0.48	0.57	347
Accuracy			0.78	1128
Macro avg.	0.75	0.70	0.71	1128
Weighted avg.	0.77	0.78	0.76	1128

ROC-AUC: 0.816

Table 14. Classification performance metrics for model (7) – Digitalized green ventures with funding below USD 1 million

	Precision	**Recall**	**F1-score**	**Support**
0.0	0.73	0.95	0.83	738
1.0	0.49	0.13	0.21	292
Accuracy			0.72	1030
Macro avg.	0.61	0.54	0.52	1030
Weighted avg.	0.67	0.72	0.65	1030

ROC-AUC: 0.687

Table 15. Classification performance metrics for model (8) – Digitalized green ventures with funding above USD 1 million

	Precision	**Recall**	**F1-score**	**Support**
0.0	0.79	0.92	0.85	738
1.0	0.72	0.44	0.55	326
Accuracy			0.78	1064
Macro avg.	0.75	0.68	0.70	1064
Weighted avg.	0.77	0.78	0.76	1064

ROC-AUC: 0.821

Overall, class imbalance remains the main driver of weak minority-class performance across all eight models. Technology-specific and embeddedness measures clearly add value for revenue and higher-tier funding outcomes, but do little to resolve the persistent difficulty in classifying lower-funding-tier ventures.

5. Conclusion

This study examined digital technology adoption among green ventures and its association with revenue and funding outcomes, combining a network-based taxonomy of digital technologies with multilevel logistic regression. Three findings emerge.

First, identifiable digital technology adoption remains limited and concentrated. Only 20.6% of ventures could be assigned to one of the six technology communities identified, and nearly three-quarters of these assignments fell within just two communities — Enterprise Software & Cloud Computing and AI & Machine Learning. More specialized technologies, including blockchain, robotics, and IoT, remained marginal. Digitalization among green ventures thus appears to rely primarily on general-purpose software and AI capabilities rather than on technologies developed specifically for environmental applications.

Second, the relationship between digitalization and venture outcomes is not uniform, and grows more differentiated as the measure of digitalization becomes more granular. Aggregate digitalization was associated with higher odds of falling in the lower revenue and funding tiers, but not the higher ones — already inconsistent with an assumption of uniformly stronger performance. Moving to VDEI sharpened this picture further: greater digital embeddedness was positively associated with both revenue tiers, negatively associated with lower-tier funding, and unrelated to higher-tier funding. Technology-specific effects diverged again — AI & ML ventures were more likely to secure smaller-scale funding but less likely to reach higher revenue, while Data & Analytics and Blockchain & Web3 were associated with lower odds of securing larger-scale funding. Taken together, whether digitalization "helps" a green venture depends on which technology is involved, how digital engagement is measured, and which outcome — revenue or funding — is in view.

Third, model discrimination was modest-to-good (ROC-AUC 0.687–0.821) but consistently weaker for minority outcome categories, especially lower-tier funding, where restricting the sample to digitalized ventures did not improve performance. The regression estimates should accordingly be read as evidence of statistical association, not as strong predictive or causal claims.

For policymakers and ecosystem support organizations, these findings caution against treating "digital adoption" as a single policy lever: since general digitalization support raises the odds

of ventures reaching modest commercial or financial thresholds but not higher-value outcomes, interventions may be more effective when targeted at specific technologies and tied to specific goals — commercial scaling versus capital access are not the same target. For entrepreneurs, the divergence between VDEI and AI & ML specifically — broad digital embeddedness tracks with revenue, AI adoption alone tracks with easier but smaller funding — suggests that technology investment should be guided by what a venture is actually trying to achieve, rather than by a general assumption that more digitalization is uniformly better.

Limitations and Future Research

Four limitations qualify these findings. First, the technology taxonomy relies on Crunchbase-assigned tags, so the large share of "non-digitalized" ventures may partly reflect incomplete public reporting rather than a true absence of digital adoption. Second, the cross-sectional design cannot establish causality: the data cannot distinguish whether digitalization drives performance, whether better-performing ventures adopt more digital technology, or whether both are shaped by unobserved organizational or market conditions. Third, class imbalance limited the models' ability to detect minority outcomes, particularly lower-tier funding; class weighting, resampling, or alternative modeling strategies could address this in future work. Fourth, longitudinal data are needed to establish the timing of digital adoption relative to performance, and disaggregating funding by source, stage, and investor type could help clarify why digital embeddedness tracks positively with revenue but diverges for funding — whether this reflects a genuine trade-off, differences in venture maturity, or simply the timing of capital raises.

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References

Ardito, L., Raby, S., Albino, V., & Bertoldi, B. (2021). The duality of digital and environmental orientations in the context of SMEs: Implications for innovation performance. *Journal of Business Research, 123*, 44–56.

Autio, E., Nambisan, S., Thomas, L. D. W., & Wright, M. (2018). Digital affordances, spatial affordances, and the genesis of entrepreneurial ecosystems. *Strategic Entrepreneurship Journal, 12*(1), 72–95.

Berger, R., Bitzer, M., Piller, F. T., & Kratzer, J. (2018). A taxonomy of technologies for digital innovation. *Proceedings of the 51st Hawaii International Conference on System Sciences*, 5465–5474.

Cohen, B., & Winn, M. I. (2007). Market imperfections, opportunity and sustainable entrepreneurship. *Journal of Business Venturing, 22*(1), 29–49.

Dalle, J.-M., den Besten, M., & Menon, C. (2017). Using Crunchbase for research: A validation study. *OECD Science, Technology and Industry Working Papers*, 2017/08. OECD Publishing.

Eller, R., Alford, P., Kallmünzer, A., & Peters, M. (2020). Antecedents, consequences, and challenges of small and medium-sized enterprise digitalization. *Journal of Business Research, 112*, 119–127.

Gelman, A., & Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press.

Geels, F. W. (2020). Micro-foundations of the multi-level perspective on socio-technical transitions: Developing a multi-dimensional model of agency through crossovers between social constructivism, evolutionary economics and neo-institutional theory. *Technological Forecasting and Social Change, 152*, 119894.

Holzmann, P., & Gregori, P. (2023). The promise of digital technologies for sustainable entrepreneurship: A systematic literature review and research agenda. *International Journal of Information Management, 68*, 102593.

Horbach, J., Rammer, C., & Rennings, K. (2012). Determinants of eco-innovations by type of environmental impact—The role of regulatory push/pull, technology push and market pull. *Ecological Economics, 78*, 112–122.

Hox, J. J. (2010). *Multilevel Analysis: Techniques and Applications* (2nd ed.). Routledge.

Kim, J., & Jin, W. (2024). Impact of digital capabilities on entrepreneurial performance in SMEs. *Journal of Innovation & Knowledge, 9*(4), 100609.

Köhler, J., Geels, F. W., Kern, F., Markard, J., Onsongo, E., Wieczorek, A., Alkemade, F., Avelino, F., Bergek, A., Boons, F., Fünfschilling, L., Hess, D., Holtz, G., Hyysalo, S., Jenkins, K., Kivimaa, P., Martiskainen, M., McMeekin, A., Mühlemeier, M. S., Nykvist, B., Papachristos, G., & Wells, P. (2019). An agenda for sustainability transitions research: State of the art and future directions. *Environmental Innovation and Societal Transitions, 31*, 1–32.

Merín-Rodrigáñez, J., Dasí, À., & Alegre, J. (2024). Digital transformation and firm performance in innovative SMEs: The mediating role of business model innovation. *Technovation, 134*, 103027.

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029–1055.

OECD. (2017). *OECD Science, Technology and Industry Scoreboard 2017: The Digital Transformation*. OECD Publishing.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods* (2nd ed.). Sage.

Shepherd, D. A., & Patzelt, H. (2011). The new field of sustainable entrepreneurship: Studying entrepreneurial action linking "what is to be sustained" with "what is to be developed." *Entrepreneurship Theory and Practice, 35*(1), 137–163.

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling* (2nd ed.). Sage.

Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice, 41*(1), 49–72.

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies, 23*(9), 1759–1769.

Sussan, F., & Acs, Z. J. (2017). The digital entrepreneurial ecosystem. *Small Business Economics, 49*(1), 55–73.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The new organizing logic of digital innovation: An agenda for information systems research. *Information Systems Research, 21*(4), 724–735. https://doi.org/10.1287/isre.1100.0322

Annex I

Table A1. Green Entrepreneurship Industry Tags

Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
Renewable Energy	754	Green Consumer Goods	100	Architecture	49
Energy	749	Social Impact	98	Wholesale	48
Manufacturing	669	Logistics	98	Power Grid	47
Software	655	Packaging Services	98	Innovation Management	47
Environmental Consulting	592	Natural Resources	97	Biomass Energy	47
Waste Management	528	Analytics	97	Mining	45
Recycling	458	Real Estate	94	Lifestyle	45
Clean Energy	416	Health Care	94	Janitorial Service	45
Environmental Engineering	365	Carbon Capture	91	Pollution Control	44
E-Commerce	355	Advanced Materials	86	Facilities Support Services	44
Consulting	339	Water Purification	84	Nutrition	43
Artificial Intelligence (AI)	334	Apps	82	Alternative Protein	42
Agriculture	331	Mobile Apps	81	Product Research	42
Information Technology	330	Communities	79	Social	42
Solar	287	Food Processing	78	Infrastructure	41
Food and Beverage	271	Oil and Gas	78	Management Consulting	41
Biotechnology	269	Business Development	78	Life Science	41
AgTech	269	Education	75	Social Entrepreneurship	41
SaaS	259	Internet	74	Smart Building	40
Energy Efficiency	226	Hardware	73	Electrical Distribution	40
Electric Vehicle	221	Commercial	73	Aquaculture	40
Farming	211	Finance	70	E-Commerce Platforms	40
Fashion	184	Organic	70	Professional Services	40
Non Profit	175	Product Design	67	Consumer Electronics	39
Retail	169	Training	67	Machinery Manufacturing	39
Transportation	167	Smart Cities	67	Information Services	38
Energy Management	162	Aerospace	65	Marketing	38
Construction	161	Impact Investing	65	Home and Garden	37
Water	157	Building Material	62	Travel	37
FinTech	155	Electronics	61	Wind Energy	36

Consumer Goods	146	Robotics	61	Compliance	36
Marketplace	145	Service Industry	59	Events	34
Automotive	139	Big Data	59	Industrial Engineering	33
Financial Services	137	Organic Food	57	Risk Management	33
Internet of Things	134	Plastics and Rubber Manufacturing	57	Customer Service	33
Blockchain	134	Textiles	57	Smart Home	32
Machine Learning	125	Sharing Economy	57	Nanotechnology	32
Industrial	117	Wellness	57	Marine Technology	32
Energy Storage	113	Forestry	56	Venture Capital	31
Supply Chain Management	112	Charging Infrastructure	55	Hospitality	31
B2B	108	Enterprise Software	54	Consumer	31
Green Building	108	Project Management	54	Property Management	31
Battery	106	Retail Technology	51	Industrial Manufacturing	31
Chemical	101	Advice	50	Chemical Engineering	31

Table A2. Green Entrepreneurship Industry Tags

Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
Residential	31	Shipping	19	Insurance	14
Cosmetics	30	Mobile	19	Charity	14
Apparel	30	Medical	19	Paper Manufacturing	13
Heating	30	Procurement	19	Computer Vision	13
Ventilation	30	Shopping	19	Mechanical Engineering	13
Air Conditioning (HVAC)	30	Public Safety	19	Delivery Service	13
Home Services	30	Delivery	18	Building Maintenance	13
Fuel	28	Laundry and Dry-cleaning	18	Sales	13
Animal Feed	28	Seafood	18	Data Management	13
Industrial Automation	28	Database	18	Property Development	13
Web3	27	Trading Platform	18	Online Portals	13
Data Visualization	27	Commercial Real Estate	17	Landscaping	13
Asset Management	27	Interior Design	17	Government	13
Tourism	27	Coffee	17	Horticulture	13
3D Technology	27	Facility Management	17	Sports	13
Predictive Analytics	26	Civil Engineering	17	Shoes	12
Cloud Computing	26	Cleaning Products	17	Technical Support	12
Rental	26	Geospatial	17	Public Transportation	12
PropTech	26	Advertising	17	Security	12
Data Center	25	Social Media	17	Real Estate Investment	12
Cryptocurrency	25	Mineral	17	Satellite Communication	12
Personal Health	25	Plant-Based Foods	16	Space Travel	12
Air Transportation	24	Lighting	16	Furniture	12
Beauty	23	Ride Sharing	16	Snack Food	11
Sensor	23	Wildlife Conservation	16	Product Management	11
Home Improvement	23	Cannabis	16	Payments	11
Grocery	22	Association	16	Data Integration	11
Semiconductor	22	Collaboration	16	GovTech	11
Subscription Service	22	Test and Measurement	16	EdTech	11
Business Intelligence	22	Telecommunications	16	Digital Media	11
Market Research	22	Small and Medium Businesses	16	Fuel Cell	11
Biofuel	22	Banking	16	Cyber Security	11
Fleet Management	22	Human Resources	16	Art	11

B2C	21	Web Development	16	Geothermal Energy	10
Marine Transportation	21	Pharmaceutical	15	Hydroelectric	10
Last Mile Transportation	21	Recruiting	15	Web Apps	10
Social Network	21	Fitness	15	Pet	10
Hydroponics	21	Medical Device	15	Parking	10
InsurTech	21	Software Engineering	15	Public Relations	10
Autonomous Vehicles	20	Productivity Tools	15	Media and Entertainment	10
Food Delivery	20	Nuclear	14	Event Management	10
Generative AI	20	Accounting	14	Digital Marketing	10
Drones	19	PaaS	14	Handmade	10
Mining Technology	19	Quality Assurance	14	Housekeeping Service	10

Table A3. Green Entrepreneurship Industry Tags

Keyword	Frequency	Keyword	Frequency	Keyword	Frequency
Outdoors	9	E-Learning	7	Non-Fungible Token (NFT)	5
Legal Tech	9	Management Information Systems	6		
Printing	9	Livestock	6		
Information and Communications Technology (ICT)	9	Gamification	6		
Brand Marketing	9	Bitcoin	6		
Cloud Data Services	9	Graphic Design	6		
Hotel	9	Remote Sensing	6		
Cloud Management	9	Water Transportation	6		
Sporting Goods	9	Field Support	6		
Travel Agency	9	Outsourcing	6		
Crowdfunding	9	Adventure Travel	6		
Wood Processing	9	Mapping Services	6		
Consumer Software	9	News	6		
Home Decor	9	Industrial Design	6		
Cycling	8	iOS	6		
Timber	8	Consumer Research	6		
Real Time	8	Car Sharing	6		
Intelligent Systems	8	Decentralized Finance (DeFi)	6		
Incubators	8	Lending	6		
Baby	8	IT Management	6		
Gift	8	Credit	6		
Personal Care and Hygiene	8	Publishing	6		
IT Infrastructure	8	Virtual Reality	6		
Freight Service	8	Railroad	5		
Computer	8	Professional Networking	5		
Corporate Training	8	Developer Platform	5		
Data Collection and Labeling	8	Home Appliances	5		
Precious Metals	8	Local Business	5		
Jewelry	7	Farmers Market	5		
Personal Development	7	Natural Language Processing	5		
Restaurants	7	Collaborative Consumption	5		

Cloud Infrastructure	7	Fruit	5		
Cooking	7	Emerging Markets	5		
Wealth Management	7	Dietary Supplements	5		
Navigation	7	UX Design	5		
Gaming	7	Leisure	5		
Developer APIs	7	Robotic Process Automation (RPA)	5		
Women's	7	Communications Infrastructure	5		
Wearables	7	Content Creators	5		
Boating	7	Creative Agency	5		
Data Mining	7	Funding Platform	5		
Loyalty Programs	7	Legal	5		

Table A4. Core Digital Technologies (Pure Digital Artifacts)

Digital Technology Keyword	Classification	Theoretical / Operational Rationale
Software / Consumer Software / Enterprise Software	Core Digital Tech	The programmable layer of digital systems, consisting of digital artifacts that enable computation, information processing, automation, and delivery of digital functionality.
Artificial Intelligence (AI) / Machine Learning	Advanced Digital Technology	Computational systems that use algorithms and data to learn patterns, make predictions, generate outputs, and support or automate decision-making.
Generative AI / Natural Language Processing / Computer Vision	Specialized AI Technology	Specialized domains of AI that enable generation, analysis, interpretation, and transformation of textual, visual, auditory, and other digital data.
Analytics / Predictive Analytics / Business Intelligence / Data Visualization	Core Digital Tech	Data-driven technologies using statistical, mathematical, and computational methods to transform data into actionable insights, support decisions, and forecast outcomes.
Database / Data Management / Data Integration / Data Collection and Labeling / Data Mining / Big Data	Core Digital Tech	Data-engineering technologies governing collection, storage, organization, integration, enrichment, and lifecycle management of digital information assets.
Cloud Computing / Cloud Data Services / Cloud Infrastructure	Core Digital Tech	Virtualized computational environments providing scalable storage, processing, networking, and data-management capabilities as digital resources.
SaaS / PaaS / Cloud Management / Developer Platform	Software-as-a-Service & Platform Architectures	Software-based service and platform architectures that support development, deployment, administration, and delivery of digital applications.
Cyber Security	Core Digital Tech	Algorithmic and cryptographic methods designed to protect the integrity, confidentiality, availability, and resilience of digital systems and information assets.
Geospatial / Remote Sensing / Mapping Services	Core Digital Tech	Spatial data-driven systems leveraging digital computation to acquire, process, analyze, and visualize location-based information from earth observation and sensing technologies.
Blockchain / Web3	Distributed Digital Infrastructure	Distributed ledger architectures enabling decentralized storage, validation, and execution of digital transactions and smart contracts.
Robotic Process Automation (RPA) / Robotics	Advanced Digital Technology	Automation technologies that combine software, sensors, control systems, and machine intelligence to execute tasks with limited human intervention.

Internet of Things / Sensor	Core Digital Tech	Networked sensing and communication technologies that capture physical signals, convert them into digital data, and enable machine-to-machine connectivity.
Virtual Reality	Advanced Digital Technology	Immersive digital environment technology that creates computer-generated interactive experiences for simulation, training, visualization, and engagement.
3D Technology	Advanced Digital Technology	The technology enabling the creation, modeling, simulation, visualization, and fabrication of three-dimensional objects and environments through computational design, rendering, digital twins, additive manufacturing, and related digital production processes.

Table A5. Digital Infrastructure and Enabling Technologies

Digital Technology Keyword	Classification	Theoretical / Operational Rationale
Hardware / Electronics / Semiconductor	Enabling Technology	Physical technological infrastructure, including semiconductor devices, electronic components, computing equipment, and communication hardware, that enables generation, processing, storage, and transmission of digital information.
Data Center / IT Infrastructure	Infrastructure	Macro-scale physical facilities housing servers, storage systems, networking equipment, cooling systems, and power architectures required for digital computation and cloud services.
Telecommunications / Satellite Communication / Communications Infrastructure	Infrastructure	Physical and electromagnetic communication networks providing connectivity and data transmission between distributed digital systems.
Information Technology / Information and Communications Technology (ICT)	Foundational Digital Technology	Broad technological domain encompassing digital computing, communications, networking, information processing, and associated software infrastructures. They carry almost no signal about *which* digital technologies are present

Table A6. Applications and Practices of Digital Technologies

Digital Technology Keyword	Classification	Theoretical / Operational Rationale
Software Engineering	Digital Capability / Practice	A discipline and development practice rather than a technology artifact itself.
Industrial Automation	Technology System / Application Domain	Too broad and often mixes software, control systems, and physical machinery.
Autonomous Vehicles	Digital Technology Application	An end-product/application domain that embeds digital technologies rather than representing a core digital technology itself.
Drones	Digital Technology Platform	A product/application platform rather than a foundational digital technology.
Cryptocurrency / Non-Fungible Token (NFT) / Decentralized Finance (DeFi)	Blockchain Applications	Blockchain-based applications, assets, or business models rather than core digital technologies.

Table A7. Modularity Comparison Across Graph Variants

Variant	Nodes	Edges	Density	Modularity (Q)	Communities
A: Raw count ≥3	34	109	0.1943	0.1030	4
B: Raw count ≥5	24	63	0.2283	0.1047	3
C: NPMI > 0	37	147	0.2207	0.4006	5

D: NPMI > 0 + count ≥3	33	57	0.1080	0.6003	6

Note. NPMI = normalized pointwise mutual information. Variant D (NPMI > 0 + count ≥3) produced the highest modularity score (Q = 0.6003) and was therefore selected as the best-performing graph specification for subsequent community detection analyses.

Table A8. Pairwise agreement between methods

Comparison	Agreement
Overlap vs. NPMI	79.3%
Overlap vs. Naive Bayes	98.3%
NPMI vs. Naive Bayes	79.4%

Note. NPMI = normalized pointwise mutual information. Pairwise agreement was calculated among ventures assigned to technology communities by the respective methods.

Table A9. Community Pair Analysis

Community Pair	Phi	Jaccard	Inter-NPMI	Relationship
AI & Machine Learning as focal community				
AI & Machine Learning × Enterprise Software & Cloud Computing	0.223***	0.154	0.041	Moderate co-adoption
AI & Machine Learning × Data & Analytics	0.174***	0.113	0.061	Moderate co-adoption
AI & Machine Learning × Robotics & 3D Tech	0.116***	0.057	0.076	Weak co-adoption
AI & Machine Learning × IoT & Sensor Systems	0.112***	0.070	0.080	Weak co-adoption
AI & Machine Learning × Blockchain & Web3	0.090***	0.058	0.000	No evidence of association
Enterprise Software & Cloud Computing as focal community				
Enterprise Software & Cloud Computing × Data & Analytics	0.164***	0.096	0.055	Moderate co-adoption
Enterprise Software & Cloud Computing × IoT & Sensor Systems	0.091***	0.053	0.029	Limited co-adoption
Enterprise Software & Cloud Computing × Blockchain & Web3	0.059***	0.040	0.070	Limited co-adoption
Remaining pairs				
Data & Analytics × IoT & Sensor Systems	0.116***	0.074	0.081	Weak co-adoption
IoT & Sensor Systems × Robotics & 3D Tech	0.053***	0.034	0.040	Limited co-adoption
Blockchain & Web3 × IoT & Sensor Systems	0.058***	0.041	0.011	Limited co-adoption
Robotics & 3D Tech × Data & Analytics	0.009	0.013	0.202	Limited co-adoption
Data & Analytics × Blockchain & Web3	0.017	0.022	0.000	No evidence of association
Robotics & 3D Tech × Enterprise Software & Cloud Computing	0.017	0.017	0.000	No evidence of association
Robotics & 3D Tech × Blockchain & Web3	0.001	0.009	0.000	No evidence of association

Table A11. Odds Ratio – Estimation Results for Green Ventures by Revenue and Funding Levels (Above and Below USD 1 Million)

Variable	Revenue_Less_1M	Revenue_More_1M	Funding_Less_1M	Funding_More_1M
	(1)	(2)	(3)	(4)
Intercept	0.017	0.026	0.341	0.065
Size	0.943	1.737	0.718	1.528
Age	1.025	1.026	0.993	0.997
Number of founders	1.407	1.255	1.716	2.344
Digitalized	1.648	0.878	1.262	1.000
Seed funding	1.821	0.924		
Early-stage venture	0.848	1.920		
M&A	1.101	0.774		
IPO	3.438	1.680		
Late-stage venture	0.180	1.003		
Private equity	0.122	0.612		

Notes: *Entries are odds ratios (exp(β)) from multi level logistic regression models. Values greater than 1 indicate higher odds of achieving the outcome, while values below 1 indicate lower odds. Funding-stage variables are included only in the revenue-based models (Columns 1–2); therefore, these entries are not applicable in the funding-based models (Columns 3–4).*

Table A12. Odds Ratio – Estimation Results for Digitalized Green Ventures by Revenue and Funding Levels (Above and Below USD 1 Million)

Variable	Revenue_Less_1M	Revenue_More_1M	Funding_Less_1M	Funding_More_1M
	(5)	(6)	(7)	(8)
Intercept	0.019	0.009	0.144	0.020
Size	0.852	1.719	0.871	2.683
Age	1.032	1.033	1.000	1.003
Number of founders	1.367	1.279	1.743	2.243
AI & ML	1.038	0.738	1.848	1.153
Software & Cloud	0.958	1.036	1.541	0.887
Robotics & RPA	0.862	0.763	1.193	0.789
Data & Analytics	1.294	1.313	1.304	0.575
Blockchain & Web3	0.979	1.032	1.194	0.549
IoT & Sensors	0.912	0.783	1.566	1.352
VDEI	3.557	4.133	0.466	1.767
Seed funding	1.289	1.382		
Early-stage venture	0.904	2.476		
M&A	0.795	1.203		
IPO	—	4.497		
Late-stage venture	0.394	1.946		
Private equity	0.660	1.355		

Notes: *Entries are odds ratios (exp(β)) from multi level logistic regression models. Values greater than 1 indicate higher odds of achieving the outcome, while values below 1 indicate lower odds. Funding-stage variables are included only in the revenue-based models (Columns 5–6); therefore, these entries are not applicable in the funding-based models (Columns 7–8).*