Review

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Configurational Factors Driving Scaling Potential for Tech-Enabled Regenerative Social Entrepreneurship

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Configurational Factors Driving Scaling Potential for Tech-Enabled Regenerative Social Entrepreneurship

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Abstract: Responding to global crises necessitates a shift towards regenerative outcomes, a goal increasingly pursued by social entrepreneurship leveraging deep technologies. Scaling the impact of such ventures presents significant challenges, highlighting the need to understand the interplay of multiple influencing factors. This study employs a mixed-method approach, integrating a literature review guided by Theories of Technological Change and Diffusion and Causal Layered Analysis with fs/QCA applied to cross-country GEM and World Bank data. The analysis sought to identify configurations of individual, organizational/activity, and contextual conditions sufficient for scaling potential proxies (early-stage entrepreneurial activity and formal venture creation). Findings reveal multiple distinct combinations of factors, demonstrating equifinality in achieving these outcomes, including conditions related to entrepreneurial perceptions, innovation, and environmental commitment. Interpreted via CLA, the results suggest configurations encompassing innovation or strong ESG commitment may hold enhanced potential for contributing to regenerative impact beyond conventional growth. The study offers insights for cultivating environments and strategies that facilitate scaled, positive socio-ecological change.

Keywords: social entrepreneurship; deep technology; impact scaling; regenerative development; fsQCA; configurational analysis; technology adoption; causal layered analysis

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1. Introduction

The contemporary world faces complex, interconnected challenges, including climate change, social inequality, and economic instability, necessitating a fundamental shift towards outcomes that are not merely sustainable but actively contribute to the regeneration and flourishing of socio-ecological systems [1,2]. Social entrepreneurship (SE), characterized by its mission to create social and environmental value alongside economic viability, stands as a crucial force in developing innovative solutions to these pressing global problems [3,4]. By applying entrepreneurial approaches to address societal needs, social entrepreneurs are uniquely positioned to drive positive change [5–10]. The potential for social entrepreneurship to achieve significant, transformative impact is increasingly enhanced by the integration of advanced digital technologies [11].

Deep technologies, such as Artificial Intelligence (AI), the Internet of Things (IoT), and Blockchain, offer transformative capabilities that can revolutionize operations, enable sophisticated analysis, enhance connectivity, and automate complex tasks [12–15]. Applied within the social sector, these technologies present significant opportunities for developing scalable solutions, improving efficiency, increasing transparency, and enabling personalized interventions [16,17]. For example, AI can optimize resource allocation for social programs or enhance data-driven decision-making [16,17], while IoT can facilitate real-time monitoring of environmental or social conditions [19], and Blockchain can increase accountability and trust in transactions and data management [19,20]. Leveraging deep technologies can significantly accelerate progress towards Sustainable Development Goals (SDGs) and contribute to regenerative outcomes [16–18].

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Despite the promising potential, scaling the positive impact of tech-enabled social ventures remains a significant challenge [21]. Scaling social impact involves unique complexities compared to traditional business growth, including navigating diverse contexts, engaging with complex stakeholder networks, and balancing social mission with economic imperatives [21,22]. For social enterprises adopting deep technologies, additional hurdles include accessing technical expertise, securing appropriate infrastructure, addressing data privacy concerns, and navigating the ethical considerations of powerful technologies in sensitive social contexts [14,16,17]. Furthermore, existing research on social entrepreneurship scaling and technology adoption often adopts linear approaches, examining individual factors in isolation [3,4,6,24]. This perspective struggles to capture the complex interplay and necessary confluence of multiple conditions that enable transformative outcomes in dynamic environments [27]. Achieving regenerative scaling, which implies a shift towards system-level restoration and flourishing [1,2], requires moving beyond isolated variables to understand configurations of factors at different levels, individual, organizational, technological, and contextual, that collectively enable this potential. This highlights a research gap in understanding the complex, multi-causal pathways to tech-driven regenerative scaling. A configurational approach, such as fuzzy-set Qualitative Comparative Analysis (fsQCA), is needed to identify these sufficient combinations of conditions [27]. Moreover, to fully grasp this phenomenon, theoretical lenses capable of addressing technological diffusion [29] and the underlying assumptions shaping the vision for technology's role in society [28] are essential to frame the problem adequately.

Drawing upon this identified gap, this study aims to identify the combinations of technological, individual, organizational, and contextual factors that are sufficient for social entrepreneurs to demonstrate scaling potential linked to the adoption of deep technologies towards regenerative futures. The research employs a configurational approach using fsQCA on publicly available data from sources such as the Global Entrepreneurship Monitor (GEM) and the World Bank (WB).

This study contributes to the literature by adopting a configurational perspective to understand the complex drivers of tech-enabled regenerative scaling, moving beyond linear models. It integrates insights from theories of Technological Change [29] and Causal Layered Analysis (CLA) [28] to offer a multi-level and multi-layered understanding of how technologies can contribute to transformative social and environmental outcomes. By focusing on regenerative potential, the study pushes the boundaries of current social impact analysis. The analysis undertaken is anticipated to provide practical insights for social entrepreneurs, technology developers, and policymakers seeking to foster a more regenerative economy through technology and social innovation.

The remainder of this paper is structured as follows: Section 2 details the methodology. Section 3 presents the empirical results, reviews relevant literature and develops the theoretical framework and conceptual model. Section 4 discusses the findings and their implications. Section 5 concludes the paper with contributions, limitations, and future research directions.

2. Materials and Methods

A mixed-method approach was employed, combining a comprehensive literature review with quantitative analysis using fuzzy-set Qualitative Comparative Analysis (fsQCA). This design facilitated both the synthesis of existing knowledge on social entrepreneurship, technology, scaling, and regenerative outcomes and the empirical investigation of complex factor configurations associated with tech-driven regenerative scaling potential.

2.1. Research Approach: Mixed-Method Design (Literature Review and fsQCA)

The research proceeded in two main phases. The first phase involved a thorough review of the existing literature to construct the theoretical framework and conceptual model presented in Section 2. This phase synthesized academic research on social entrepreneurship's evolution, the challenges and methods of scaling social impact, the application of deep technologies in the social sector, and relevant theoretical lenses, specifically Theories of Technological Change and Diffusion and Causal Layered Analysis. Insights gained during this review guided the selection and framing of variables

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for subsequent quantitative analysis. The second phase applied fsQCA to cross-country data to identify combinations of individual, organizational, activity, and contextual conditions sufficient for the outcome of tech-driven regenerative scaling potential, as represented by available data proxies.

2.2. Data Sources and Merging

The quantitative analysis utilises publicly available secondary data from two primary sources: the Global Entrepreneurship Monitor (GEM) and the World Bank Entrepreneurship Data.

2.2.1. Literature Review Process

Academic databases such as Scopus and Web of Science were searched using keywords drawn from the study's core concepts, including "social entrepreneurship," "social innovation," "scaling social impact," "regenerative development," "deep technology" (and specific types like "Artificial Intelligence," "Internet of Things," "Blockchain"), "technology adoption," "Diffusion of Innovations," and "Causal Layered Analysis." Relevant peer-reviewed publications were identified. Inclusion criteria focused on English-language literature pertinent to the intersection of social entrepreneurship, technology, scaling, and regeneration, or providing foundational theoretical insights. Publications outside these criteria or lacking theoretical/empirical depth were excluded. This process yielded the body of literature discussed earlier.

2.2.2. Quantitative Data: Global Entrepreneurship Monitor (GEM) and World Bank Entrepreneurship Data

Quantitative data was obtained from the Global Entrepreneurship Monitor (GEM), which provides detailed insights into entrepreneurial activity and attitudes, and the World Bank Entrepreneurship Data, offering business registration indicators. Country-year observations were extracted from both sources. Variables selected for fsQCA were chosen based on the conceptual framework (Section 2.5) to serve as proxies for individual (adult_population, perceived_opportunities, perceived_capabilities, fear_failure_rate, high_status_successful_entrepreneurs, entrepreneurship_good_career_choice), organizational/activity (number_entrepreneur_llc, new_business_density_rate, entrepreneurial_tea, established_business_ownership, entrepreneurial_employee_activity, Innovation), and contextual (new_business_density_rate, adult_population, EGCC) conditions. Data covering the most recent available years for common countries across both datasets formed the basis for the cross-country analysis.

2.2.3. Data Merging and Preparation Process

Data from GEM and the World Bank were merged using country and year as keys. Standardizing country names and handling missing values were part of this process. Variables relevant to the conceptual framework were extracted and prepared, including checks on data types and distributions. Acknowleging the absence of direct, large-scale data on deep technology adoption by social enterprises or explicit regenerative outcomes, the analysis relies on proxies related to overall entrepreneurial dynamism, innovation, and conducive environmental factors as delineated in the conceptual framework. Data merging, cleaning, and initial variable preparation steps were facilitated by a Python script. All data used is publicly accessible through the respective organizations.

2.3. Fuzzy-Set Qualitative Comparative Analysis (fsQCA)

Fuzzy-set Qualitative Comparative Analysis (fsQCA) served as the main analytical method for the quantitative data.

2.3.1. Rationale for fsQCA

Fs/QCA was selected for its capacity to analyze complex causal relationships in medium-sized datasets typical of cross-country studies [27]. Unlike linear models, fs/QCA identifies combinations

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of conditions sufficient for an outcome, aligning with the study's view that tech-driven regenerative scaling potential results from specific configurations rather than single factors [27]. The method supports the principle of equifinality, allowing for different condition combinations to achieve the same outcome, and facilitates the identification of necessary and sufficient conditions.

2.3.2. Case Selection

The unit of analysis was the Country-Year. Data points were selected for specific years with overlap between datasets. After merging and preparation, the analysis included country-year observations with complete data across all selected variables, resulting in N > 100 cases, appropriate for fs/QCA.

2.3.3. Outcome and Condition Selection

Drawing from the conceptual framework (Section 2.5) and considering data availability, two outcome variables were chosen as proxies for scaling potential within entrepreneurial ecosystems relevant to tech-driven initiatives. These proxy outcomes were: Total Early-Stage Entrepreneurial Activity (entrepreneurial_tea, also referred to as High_E_TEA), representing the rate of new ventures indicative of a dynamic entrepreneurial environment [26]; and Number of Entrepreneurs Forming Limited Liability Companies (number_entrepreneur_llc, or Num_Entrepreneur_LLC), reflecting the rate of formal business creation as a sign of scaling intent and structure [40]. These variables indicate an entrepreneurial landscape with potential conducive to growth and formalization.

The conditions entering the fs/QCA models include variables proxying individual-level factors (Perceived Opportunity, Perceived Capability, Fear of Failure Rate), organizational/activity-level factors (Entrepreneurial Behavior Opportunity, Innovation), and contextual-level factors (Adult Population, New Business Density Rate, High Social Status Entrepreneurship, Environmental, Social, and Governance Commitment & Consciousness). These were chosen as the most relevant indicators available in the datasets to represent the layers and factors hypothesized to influence the outcome.

2.3.4. Calibration Strategy

Raw data for conditions and outcomes were transformed into fuzzy-set membership scores between 0 (full non-membership) and 1 (full membership) using the direct method [27]. This involved defining three qualitative anchors: full non-membership (set to the 5th percentile of the data distribution), the crossover point (set to the 50th percentile or median), and full membership (set to the 95th percentile). This percentile-based approach is a standard practice for calibrating continuous variables in fs/QCA [27]. Specific anchor values used for each calibrated variable are available upon request. Variables lacking sufficient variation were excluded from the analysis.

2.3.5. Analysis Procedure

Following calibration, a truth table was constructed for each outcome, listing all possible combinations of calibrated conditions and their association with the outcome's presence. The truth table was filtered using a frequency threshold of 1, considering only configurations observed in at least one case. A consistency threshold of 0.80 was applied, deeming a configuration sufficient if the outcome was present in at least 80% of cases exhibiting that combination [27]. The Quine-McCluskey algorithm generated Boolean solutions. The Intermediate solution, incorporating conditions from the Parsimonious solution and those passing a necessity test for intermediate derivation, was selected for interpretation due to its balance of logical minimization and empirical support [27]. The fs/QCA software package (version 4.1) was used for the analysis.

3. Results

This section presents the findings from the analysis. It begins with descriptive statistics of the variables used in the quantitative phase, followed by the results of the fs/QCA for the two outcome variables. A synthesis of key findings from the literature review, relevant to interpreting these results, is also included as guided by the specified structure.

3.1. Descriptive Analysis

Table 1 presents the descriptive statistics for the raw, pre-calibrated variables used in the fsQCA. The table includes the mean, standard deviation, minimum, and maximum values for each variable across the analyzed country-year cases.

Table 1. Descriptive Statistics of Variables (Pre-Calibration).

Variable	Mean	Std. Dev.	Minimum	Maximum
adult_population	19752610	73038500	6022	960800000
number_entrepreneur_llc	30117	76650	2	790310
new_business_density_rate	5.32	22.08	0.01	377.82
perceived_opportunities	48.07	7.94	7.27	95.38
perceived_capabilities	53.65	7.05	10.05	92.63
fear_failure_rate	40.10	4.92	7.14	75.42
entrepreneurial_tea	11.41	3.76	1.56	49.60
established_business_ownership	7.00	2.39	1.25	35.94
entrepreneurial_employee_activity	1.80	1.32	0.00	11.47
Innovation	9.33	7.51	0.00	58.70
high_status_successful_entrepreneurs	71.42	6.95	0.00	96.73
entrepreneurship_good_career_choice	64.94	7.76	0.00	96.55

The statistics show considerable variation across the analyzed country-years for most variables, reflecting the diversity of entrepreneurial ecosystems and country characteristics captured in the dataset. Variables like adult_population, number_entrepreneur_llc, and new_business_density_rate exhibit very large standard deviations relative to their means, indicating skewed distributions typical of country-level demographic and economic data. Perception-based variables from GEM (perceived_opportunities, perceived_capabilities, fear_failure_rate, high_status_successful_entrepreneurs, entrepreneurship_good_career_choice) show smaller standard deviations, suggesting more clustering around the mean for these attitudinal measures across countries.

3.1.1. Decoding: fsQCA Results (Outcome: High_E_TEA)

Table 2 presents the fsQCA intermediate solution for the outcome High_E_TEA (Total Early-Stage Entrepreneurial Activity). The analysis identified several combinations of conditions that are sufficient for high levels of early-stage entrepreneurial activity, serving as a proxy for scaling potential. The consistency threshold was set at 0.80, and the frequency threshold at 1.

Table 1. fsQCA Results - Model: High_E_TEA = f(Adult_Pop, new_BDR, PO, PC, FFR, innovate, high_SSE, EGCC).

Adult_Pop	new_BDR	PO	PC	FFR	innovate	high_SSE	EGCC	Raw Coverage	Consistency
o	o	~	~	*	~	o	o	0.85	0.97
*	o	~	~	o	o	~	~	0.43	0.95
*	~	~	~	o	~	o	o	0.40	0.96

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o	*	~	~	~	o	o	~	0.55	0.97
~	*	o	~	o	o	~	~	0.55	0.93
~	*	o	~	o	~	o	~	0.55	0.91
~	~	*	*	o	~	o	o	0.54	0.99
~	*	o	~	*	o	o	~	0.53	0.97
~	~	*	o	o	~	*	o	0.57	0.98
~	o	o	o	*	~	*	*	0.60	0.98
o	~	~	o	~	~	~	~	0.65	0.98
*	~	~	~	~	~	~	o	0.38	0.98
~	*	~	o	o	~	~	~	0.54	0.96
~	~	~	o	~	*	~	~	0.04	0.91
~	~	~	o	~	~	*	~	0.55	0.99
~	~	~	o	~	~	~	*	0.50	0.99
o	*	o	~	*	~	~	~	0.54	0.97
~	o	*	o	*	~	~	~	0.69	0.99
~	*	~	~	o	~	*	~	0.47	0.98
o	~	*	*	*	~	o	~	0.55	0.99
*	*	*	~	~	~	o	*	0.35	0.99
*	*	*	*	~	o	~	o	0.24	0.99
o	~	*	o	*	~	*	*	0.54	0.99
Solution Coverage			0.94						
Solution Consistency			0.90						

Note: Outcome = High_E_TEA. Algorithm = Quine-McCluskey. Consistency Cutoff = 0.80. Frequency Cutoff = 1. (*) = Condition Present; (~) = Condition Absent; (o) = Condition Don't Care. Raw Coverage = proportion of the outcome explained; Consistency = reliability of the path.

The solution identifies multiple pathways, consisting of different combinations of the analyzed conditions, that are sufficient for achieving high levels of early-stage entrepreneurial activity. Each row in the table represents a distinct configuration. The raw coverage indicates the proportion of cases with the outcome that are explained by a particular configuration. The consistency indicates the degree to which the cases displaying the configuration also exhibit the outcome. The overall solution coverage of 0.94 indicates that 94% of the cases with high High_E_TEA are explained by the identified configurations. The overall solution consistency of 0.90 indicates a high degree of reliability in the identified pathways.

3.1.2. Understanding: fsQCA Results (Outcome: Num_Entrepreneur_LLC)

Table 3 presents the fsQCA intermediate solution for the outcome Num_Entrepreneur_LLC (Number of Entrepreneurs Forming Limited Liability Companies). The analysis sought to identify combinations of conditions sufficient for high numbers of formal business registrations, serving as another proxy for scaling potential and organizational formalization. The consistency threshold was set at 0.80, and the frequency threshold at 1.

Table 2. fsQCA Results – Model: Num_Entrepreneur_LLC = f(Adult_Pop, new_BDR, PO, PC, EBO, innovate).

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Adult_Pop	new_BDR	PO	PC	EBO	innovate	Raw Coverage	Consistency
*	o	o	o	o	~	0.54	0.89
~	o	o	~	o	*	0.07	0.95
o	*	o	*	~	~	0.44	0.82
~	~	o	o	*	*	0.04	0.98
o	*	*	o	*	~	0.43	0.82
*	*	*	*	*	o	0.27	1
*	o	~	~	o	o	0.47	0.91
o	o	~	~	o	*	0.08	0.98
o	*	o	~	*	~	0.45	0.82
~	*	o	~	*	o	0.43	0.82
Solution Coverage			0.75				
Solution Consistency			0.82				

Note: Outcome = Num_Entrepreneur_LLC. Algorithm = Quine-McCluskey. Consistency Cutoff = 0.80. Frequency Cutoff = 1. (*) = Condition Present; (~) = Condition Absent; (o) = Condition Don't Care. Raw Coverage = proportion of the outcome explained; Consistency = reliability of the path.

Similarly, Table 3 presents multiple sufficient configurations for achieving a high number of registered limited liability companies. Each row denotes a specific combination of conditions associated with this outcome. The raw coverage indicates the proportion of cases with the outcome accounted for by a given configuration, while consistency reflects the degree to which the configuration leads to the outcome. The overall solution coverage of 0.82 indicates that 82% of the cases with a high number of registered LLCs are explained by these configurations. The overall solution consistency of 0.82 indicates a reliable association between the identified pathways and the outcome.

3.2. Literature Review and Theoretical Framework

This section provides a comprehensive review of the literature relevant to the study of social entrepreneurship, the scaling of social impact, and the role of deep technologies. It also lays the theoretical groundwork for comprehending the complex interaction of elements that can lead to technology-driven regenerative scaling, which culminates in a conceptual framework.

3.2.1. Defining Social Entrepreneurship and the Shift Towards Regenerative Outcomes

Social entrepreneurship is widely understood as the process of pursuing innovative solutions to societal problems with a primary emphasis on creating social value [3,4,10,32]. Distinct from traditional commercial entrepreneurship, social enterprises blend social mission with entrepreneurial strategies, operating across various legal and organizational forms, including non-profit, for-profit, and hybrid structures [32,33]. The core purpose is to address unmet social needs or environmental challenges [3,4]. This focus on positive impact, often termed "social innovation" [32,35], is the defining characteristic of social entrepreneurship.

The increasing urgency of global challenges, particularly climate change and systemic inequalities, highlights the need to move beyond traditional concepts of sustainability, which often focus on minimizing harm or maintaining current states [1,2]. A growing imperative is the pursuit of regenerative outcomes, aiming not just to sustain but to actively restore, replenish, and foster the thriving of social, ecological, and economic systems [1,2]. This regenerative paradigm goes beyond simply "doing less harm" or even "doing no harm" to strive for a "net positive" contribution,

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rebuilding capacity and enhancing resilience within these systems [1,2]. For social enterprises, this implies a shift in focus from measuring isolated impacts (e.g., number of beneficiaries served) to understanding and contributing to system-level health and vitality [1,2,36]. Regenerative value creation requires engaging with the root causes of problems and transforming underlying systems, which is inherently more complex than achieving incremental improvements [1,2,37]. Social entrepreneurship, with its foundational commitment to social good, is inherently aligned with this regenerative ambition, yet translating this aspiration into scaled reality presents significant challenges [11,22]. The shift towards regenerative outcomes also necessitates the development of new metrics and evaluation frameworks that can capture systemic change and long-term well-being, moving beyond traditional impact measurement approaches [8,36].

3.2.2. Scaling Social Impact: Models, Challenges, and the Role of Technology

Scaling social impact refers to the process by which social enterprises expand their reach and depth of positive social or environmental change [21]. Various models exist to achieve this, including direct replication of successful ventures, disseminating knowledge and best practices (diffusion), influencing policies and systems (advocacy), and working to transform the root causes of problems (systemic change) [21]. Each of these approaches involves distinct strategies and faces unique challenges. Common difficulties in scaling social impact include mobilizing sufficient financial and human resources, adapting the model to diverse cultural and contextual nuances, and managing the inherent tension between growth pressures and maintaining the core social mission, often referred to as mission drift [21,22]. Successfully scaling social impact often requires navigating complex relationships with diverse stakeholders, including beneficiaries, governments, funders, and other organizations [7,38].

Technology has long been recognized as a powerful enabler for scaling operations and impact across various sectors [16,17]. Digital technologies, in particular, can significantly enhance communication, expand the reach of services, improve operational efficiency, and provide essential tools for data collection, analysis, and reporting, which are vital for demonstrating and managing social impact [14,15]. For social enterprises, technology offers pathways to connect with a broader base of beneficiaries and stakeholders, deliver programs and services more efficiently across dispersed geographies, manage complex operations, and collect necessary data to measure progress towards their social goals [14–16]. The potential of technology to accelerate and deepen social change is widely acknowledged in the literature [16,17,19].

3.2.3. The Social Sector and Deep Technologies (AI, IoT, Blockchain, etc.)

Deep technologies are a collection of advanced and often intricate technological innovations that have the potential to significantly alter society and the economy [12,16]. The Internet of Things (IoT), blockchain, sophisticated robotics, biotechnology, and artificial intelligence (AI) are all included in this category [13]. Focusing on digital and data-centric applications pertinent to expanding social ventures, this study primarily considers AI, IoT, and Blockchain as key deep technologies [13,16,17,19,20].

AI encompasses developing computer systems capable of doing activities that have historically required human intelligence, such as learning, problem solving, and decision making, and typically includes machine learning and natural language processing [16,17]. IoT consists of networked physical devices equipped with sensors, software, and network capabilities that may collect and share data for better monitoring, control, and automation of physical systems [17,19]. Blockchain technology creates a decentralized and distributed ledger for securely, transparently, and immutably recording transactions or digital information, fostering trust and accountability among numerous participants without requiring a central authority [19,20].

These deep technologies offer specific, high-potential applications for addressing critical social and environmental challenges. Artificial Intelligence, for example, can help social enterprises by analyzing large datasets to detect patterns and estimate future requirements in areas such as

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healthcare, education, and social services [16,17]. It can also automate routine administrative tasks, freeing up resources for mission-critical activities, enhance diagnostic abilities [16], optimize supply chains for greater efficiency and impact [19], or deliver personalized learning or support to individuals [17]. The Internet of Things provides capacities for monitoring in real-time within various social impact domains, such as tracking environmental pollution or resource consumption levels [19]. It can also support the management of smart infrastructure in communities, optimize energy usage in social housing, or facilitate remote health monitoring for vulnerable populations [16]. Blockchain technology offers uses for creating transparent and trackable systems for managing aid distribution and donations [20], ensuring ethical sourcing and fair trade within supply chains [19,20], verifying the authenticity of services or products, or establishing secure digital identities for marginalized individuals lacking traditional documentation. Emerging examples of "Deep Tech for Good" initiatives around the world demonstrate the concrete potential of these technologies to significantly enhance the effectiveness and reach of social interventions and contribute to SDGs [16–20]. These applications underscore the critical role deep technologies can play as powerful tools for social entrepreneurs aiming to scale their impact and contribute to broader systemic change [16–20].

3.3. Theoretical Foundations

Understanding the complex pathways through which social enterprises can leverage deep technologies to achieve regenerative scaling potential requires an integrated theoretical perspective that accounts for technological adoption processes and the influence of underlying worldviews. This study draws upon two key theoretical lenses: Theories of Technological Change and Diffusion and Causal Layered Analysis (CLA).

3.3.1. Theories on Technological Change and Diffusion

Theories of technological change and dissemination, such as Everett Rogers' fundamental dissemination of Innovations hypothesis [29], lay the groundwork for understanding how new technologies spread and are adopted by individuals and institutions. Rogers' framework emphasizes the significance of the perceived characteristics of the innovation itself (e.g., relative advantage, compatibility, complexity, trialability, and observability), the characteristics of potential adopters, the communication channels used, and the social system in which diffusion occurs [29]. Adaptations to the Technology Acceptance Model (TAM) emphasize the importance of individual perceptions, notably perceived usefulness and ease of use, as significant determinants of technology adoption behavior [29].

These theories are highly relevant for analyzing the adoption of deep technologies by social entrepreneurs and their organizations. The perceived ability of a deep technology to significantly advance a social mission (perceived usefulness/relative advantage), the perceived difficulty of integrating complex tech solutions (complexity/ease of use), the alignment of the technology with the social enterprise's existing practices and values (compatibility), and the ability to experiment with the technology on a smaller scale (trialability) all influence adoption decisions [24,29]. Individual characteristics of social entrepreneurs, such as their prior experience with technology, entrepreneurial self-efficacy, and risk tolerance, also play a role [4,6,24]. At the organizational level, factors such as access to financial resources, the availability of technical skills within the team, and an organizational culture that encourages innovation and experimentation are critical enablers [24,25]. The concept of "bricolage," where entrepreneurs creatively combine existing resources in novel ways [25], is particularly pertinent for resource-constrained social enterprises attempting to adopt or adapt complex deep technologies. Understanding these micro and meso-level adoption processes is crucial for explaining the initial condition of tech adoption, which precedes the potential for tech-driven scaling. The diffusion of social innovations itself shares many characteristics with technology diffusion, emphasizing the role of networks and communication [23].

3.3.2. Causal Layered Analysis (CLA)

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Causal Layered Analysis (CLA), developed by Sohail Inayatullah, is a method for deconstructing complex issues and understanding potential futures by examining different levels of reality [28]. CLA moves beyond surface-level descriptions to explore the deeper structural causes, worldviews, and underlying myths that shape a problem or a phenomenon [28]. This approach identifies four layers: the Litany, representing the most visible, day-to-day issues often presented as problems or trends (e.g., statistics on poverty, pollution levels, instances of social exclusion) [28]. These are often what social enterprises directly respond to. Below the Litany is the Systemic level, encompassing the social, economic, political, and technological structures, processes, and institutions that contribute to the Litany [28], including policies, laws, market dynamics, and infrastructure (including digital infrastructure). Deeper still is the Worldview layer, which consists of the underlying beliefs, assumptions, values, and mental models that shape how individuals and societies perceive reality, legitimate the Systemic structures, and define what is considered desirable or possible [28], with examples including beliefs in linear progress, individualism, anthropocentrism, or the separation of economy and environment. The deepest layer is Myth/Metaphor, consisting of unconscious narratives, archetypes, and stories that inform and reinforce the Worldviews [28], often deeply embedded cultural or historical narratives like the myth of perpetual economic growth or the hero's journey of the lone entrepreneur overcoming all odds.

Applying CLA is crucial for differentiating social entrepreneurship activities that merely address symptoms within the existing system from those that seek to achieve genuinely regenerative outcomes by challenging and transforming deeper structures and beliefs [1,2,37]. While deep technologies can be applied at the Systemic level to improve efficiency or create new solutions (addressing the Litany), their potential for regenerative impact depends on the underlying Worldviews and Myths that guide their development and deployment [1,2,28]. For instance, using AI within a Systemic framework might optimize resource extraction for profit (reinforcing a worldview of resource exploitation). A regenerative approach, informed by a different worldview (e.g., ecological stewardship), might use the same technology to facilitate community-based resource management or design closed-loop systems [1,2,18]. CLA helps to reveal whether the vision guiding the use of deep tech is one of simply mitigating harm or one of actively restoring and enhancing the vitality of systems [1,2,37]. This theoretical lens is vital for framing the outcome variable as "regenerative scaling potential," as it requires examining factors that might indicate a departure from conventional approaches driven by unsustainable worldviews.

3.3.3. Conceptual Framework: Factors Influencing Tech-Driven Regenerative Scaling

Building on the literature review and the integrated theoretical foundations, this study proposes a conceptual framework illustrating the interplay of technological, individual, organizational, and contextual factors that are hypothesized to influence the potential for social entrepreneurs to achieve scaled, regenerative impact through deep technology adoption. This framework recognizes that successful outcomes are likely the result of specific combinations of conditions rather than single dominant factors [27]. The theoretical lenses inform the selection and interpretation of these conditions: Technological Change theories highlight the importance of individual and organizational readiness and adoption processes [24,29]; and CLA underscores the significance of underlying perspectives for achieving truly regenerative outcomes [1,2,28].

Based on the theoretical synthesis and considering the types of data available in global datasets like the Global Entrepreneurship Monitor (GEM) and the World Bank (WB), key conditions hypothesized to influence Tech-Driven Regenerative Scaling Potential (Outcome) are identified. These conditions operate at different levels. Individual-level conditions, reflecting the characteristics of the social entrepreneur, are proxied by GEM data capturing individual perceptions and intentions. These include Perceived Opportunity (PO), representing the entrepreneur's belief in identifying opportunities for new businesses, potentially including those addressing social needs with technology [26]; Perceived Capability (PC), the entrepreneur's confidence in their skills and knowledge to start and run a business, relevant for navigating the complexities of social

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entrepreneurship and deep tech adoption [6,26]; and Fear of Failure Rate (FFR), a measure of how much the fear of failure inhibits entrepreneurial activity, where lower fear may correlate with a greater willingness to pursue innovative, potentially riskier tech-enabled ventures [26].

Organizational/Activity-level conditions reflect entrepreneurial activity and innovation capacity, proxied by GEM and potentially WB data related to entrepreneurial dynamism and innovation. These include Entrepreneurial Behavior Opportunity (EBO), indicating the prevalence of individuals actively engaged in starting a new business, where a higher rate suggests a more dynamic entrepreneurial environment [26]; Total Early-Stage Entrepreneurial Activity (TEA), the overall rate of nascent and new entrepreneurs, a broad indicator of entrepreneurial vitality [26]; and Innovation, represented by national or regional indicators (e.g., R&D expenditure, patent applications, innovation surveys) serving as proxies for the prevalence of innovative activity and the capacity for adopting new approaches, including technological ones [19]. While firm-level innovation data would be ideal, these broader indicators provide a relevant context.

Contextual-level conditions reflect the broader environment and system, proxied by WB and potentially GEM data capturing macro-level factors. These encompass Adult Population (Adult_Pop), the size of the adult population as a proxy for market size and workforce; New Business Density Rate (new_BDR), the rate of new business registrations per capita, reflecting the ease of starting businesses and the vibrancy of the entrepreneurial ecosystem [40]; High Social Status Entrepreneurship (high_SSE), the extent to which entrepreneurship is perceived positively, potentially indicating a more supportive cultural environment attracting skilled individuals [26]; and Environmental, Social, and Governance Commitment & Consciousness (EGCC), a measure reflecting a country's or region's commitment to ESG principles, potentially indicating a landscape favorable to ventures with strong social/environmental missions and supportive policies for regenerative initiatives [1,2]. Technology Proxies are implicitly captured through conditions like Innovation and New Business Density Rate, reflecting the prevalence of technological development and adoption [17,19], due to limitations on direct deep technology adoption data for social enterprises in global datasets like GEM/WB.

The proposed conceptual framework posits that Tech-Driven Regenerative Scaling Potential (Outcome) is achieved through different combinations (configurations) of these Individual, Organizational/Activity, Contextual, and Technology-proxied conditions. For instance, high Perceived Capability, strong New Business Density, and high Innovation might be one pathway, while high Perceived Opportunity, strong EGCC, and supportive Entrepreneurial Behavior might constitute another. fsQCA will be employed to identify these sufficient configurations, moving beyond linear models to understand the multiple recipes for success in leveraging deep tech for regenerative social impact.

3.3.4. Key Findings from the Literature Review

The literature review synthesizes understanding across several domains critical to this study. It highlights that social entrepreneurship is primarily distinguished by its focus on social and environmental value creation alongside economic viability [3,4,10,32]. A significant theme is the growing imperative to move beyond sustainability to regenerative outcomes, aiming for system-level restoration and flourishing rather than merely minimizing harm [1,2]. Scaling social impact is identified as a complex process involving various models like diffusion and systemic change, fraught with challenges related to resources, context adaptation, and mission preservation [21,22]. Technology, particularly digital and deep technologies like AI, IoT, and Blockchain, is consistently presented as a potent enabler for scaling, enhancing efficiency, reach, and data management for social ventures [14,16,17,19,20]. These technologies offer diverse applications from optimizing service delivery with AI to ensuring transparency with Blockchain and enabling monitoring with IoT [16,17,19,20]. However, the literature also implicitly and explicitly points to the fact that the transformative potential of technology is mediated not just by technical capabilities but by the organizational, individual, and broader contextual factors influencing their adoption and application.

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Furthermore, the literature indicates that achieving truly regenerative outcomes necessitates a shift in underlying perspectives and structures, a point illuminated by frameworks like Causal Layered Analysis [1,2,28]. The synthesis confirms the need for a multi-faceted approach to understanding how technology contributes to scaled, positive impact, requiring consideration of factors beyond the technology itself, and recognizing the potential for different combinations of conditions to lead to similar outcomes.

4. Discussion

This study employed a mixed-method approach, combining a literature review with fsQCA, to identify combinations of factors associated with tech-driven regenerative scaling potential in social entrepreneurship. The fsQCA results provide insights into the complex, equifinal pathways that may lead to a dynamic entrepreneurial ecosystem and the formation of formal ventures, serving as proxies for scaling potential conducive to leveraging deep technologies for regenerative outcomes.

4.1. Insights from the Configurations for Scaling Regenerative Social Entrepreneurship

The fsQCA analysis for the outcome High_E_TEA (Total Early-Stage Entrepreneurial Activity), a proxy for a dynamic entrepreneurial environment where tech-enabled social ventures can emerge and potentially scale, reveals multiple sufficient configurations (Table 2). Notably, high Perceived Capability (PC) appears frequently across different pathways, often in combination with other conditions. This suggests that entrepreneurs' confidence in their skills is a recurring element in environments with high rates of new venture creation, aligning with literature on entrepreneurial readiness [6,26]. Similarly, high Perceived Opportunity (PO) is present in several paths, indicating that the perception of favorable business opportunities is also conducive to this outcome [26]. Low Fear of Failure (~FFR) also features in some configurations, suggesting that a reduction in risk aversion can facilitate new venture formation [26]. Innovation (innovate) appears in some, but not all, pathways, indicating that a high rate of early-stage entrepreneurial activity is not solely dependent on formal innovation inputs. Some pathways highlight the importance of high Social Status Entrepreneurship (high_SSE) or high Environmental, Social, and Governance Commitment & Consciousness (EGCC), reflecting the influence of cultural and environmental contexts. The diversity of these pathways underscores the principle of equifinality; different combinations of individual, activity, and contextual factors can lead to similar levels of new entrepreneurial activity.

For the outcome Num_Entrepreneur_LLC (Number of Entrepreneurs Forming Limited Liability Companies), a proxy for formal organizational scaling intent, the fsQCA results also show multiple sufficient configurations (Table 3). High Perceived Opportunity (PO) is a prominent condition across many pathways, suggesting that the perception of viable opportunities is crucial for the formalization and growth of ventures [26]. High New Business Density Rate (new_BDR), reflecting an environment with ease of starting businesses and active entrepreneurial ecosystems, appears in several configurations, sometimes in combination with high PC or high EBO (Entrepreneurial Behavior Opportunity) [40]. Innovation (innovate) is present in some pathways, indicating its role in formal venture creation, but again, not in all. The Adult Population (Adult_Pop) appears as a condition or is absent depending on the pathway, suggesting its influence is context-dependent. These findings align with literature on the factors influencing entrepreneurial activity and formalization, emphasizing both individual perceptions and the enabling environment [4,6,26,40].

Interpreting these findings through the theoretical lenses provides deeper insights. Theories of Technological Change and Diffusion [29] highlight that the adoption and spread of innovations depend on characteristics of the innovation, adopters, and the social system. The consistent presence of high Perceived Capability and Perceived Opportunity in pathways to scaling proxies aligns with the "adopter characteristics" and "perceived usefulness/advantage" aspects of adoption theories; entrepreneurs confident in their abilities and seeing opportunities are more likely to adopt and leverage technologies for growth [24]. Environmental factors like new_BDR and high_SSE can be

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seen as aspects of the "social system" that facilitate entrepreneurial activity and potentially technology diffusion within that system.

Causal Layered Analysis (CLA) provides a lens for interpreting the potential for regenerative scaling. The presence of configurations leading to scaling proxies without high innovation or high EGCC is particularly insightful [1,2,19]. While these pathways may lead to scale (addressing the Litany and operating within the Systemic level), their potential for regenerative impact (challenging Worldviews/Myths) may differ from pathways that include high innovation or high EGCC. Innovation, especially radical or deep tech innovation, can potentially disrupt existing Systemic structures and enable new practices aligned with regenerative worldviews [18]. High EGCC directly reflects a societal commitment to environmental and social principles, indicative of a landscape where regenerative worldviews may be more prevalent or supported [1,2]. Thus, achieving scale through configurations lacking these conditions might represent growth within the existing, potentially unsustainable, Systemic and Worldview frameworks, whereas configurations including innovation and EGCC may indicate a greater potential for contributing to genuinely regenerative change.

4.2. Theoretical Contributions

The study contributes to the literature by moving beyond linear analyses to adopt a configurational perspective via fsQCA, offering a more nuanced understanding of the multiple pathways to scaling potential in social entrepreneurship. By focusing on scaling potential conducive to leveraging deep technologies for regenerative futures, it extends existing research on social entrepreneurship, scaling, and technology adoption, which often treats these concepts in isolation or focuses primarily on traditional business growth models. The integration of Theories of Technological Change and Diffusion provides insight into the adoption readiness within these pathways, while the application of Causal Layered Analysis offers a multi-layered interpretation of the quality of scaling potential, distinguishing between growth within existing systems and potential for genuinely regenerative transformation. This integrative theoretical approach contributes to a richer conceptualization of how technological potential, individual agency, and environmental context interact to foster regenerative outcomes in social ventures.

4.3. Practical Implications

The findings offer practical insights for various stakeholders. For social entrepreneurs, the existence of multiple sufficient configurations suggests flexibility in strategy. Rather than striving for a single ideal profile, entrepreneurs can focus on cultivating specific sets of conditions relevant to their context – perhaps leveraging strong perceived capabilities and an innovative approach in one environment, or capitalizing on strong perceived opportunities and supportive community networks in another. Identifying the core conditions in the relevant pathways can guide strategic choices regarding skill development, team building, and seeking external partnerships or resources.

For investors and funders, the identified configurations provide a framework for assessing scaling potential beyond traditional business metrics. The findings suggest looking for specific combinations of entrepreneurial characteristics, organizational capacity indicators (like innovation inputs or formalization intent), and contextual factors (like new business density or ESG commitment) that signal a conducive environment for tech-enabled growth. Recognizing diverse pathways can help identify promising ventures in varied ecosystems.

Policymakers can use these results to design more effective support programs. Understanding which combinations of conditions are sufficient highlights levers for intervention. Policies could target improving perceived capabilities and opportunities through education and training, fostering innovation ecosystems, reducing barriers to formal business registration, and promoting entrepreneurship's social status. Furthermore, policies supporting ESG commitment can create a more favorable landscape for ventures with strong social and environmental missions, potentially aligning scaling efforts with regenerative goals. Addressing the specific challenges of deep tech adoption in the social sector, such as access to expertise and infrastructure, can also be informed by understanding the characteristics of environments where scaling potential is already present.

For technology developers, insights into the factors facilitating scaling potential can inform the design of deep tech solutions. Technologies that are compatible with entrepreneurs' perceived capabilities and integrate well into existing or emerging organizational structures and supportive environmental conditions are more likely to be adopted and leveraged effectively for impact. Designing technologies with inherent features that support transparency (Blockchain), data-driven decision-making (AI), or resource efficiency (IoT) can align technical capability with the potential for regenerative outcomes, particularly when deployed within conducive contexts.

4.4. Limitations and Future Research Directions

This study is subject to several limitations. First, data limitations necessitate the use of macro-level variables as proxies for firm-level characteristics and the complex phenomenon of "tech-driven regenerative scaling potential." Direct measures of deep technology adoption by social enterprises and validated indicators of regenerative outcomes at scale are not readily available in large, cross-country datasets like GEM and WB. This limits the ability to draw definitive causal links between specific deep tech applications and measured regenerative impact. Second, the calibration choices inherent in fsQCA can influence results, although standard percentile-based methods were used. Third, the cross-sectional nature of the available data limits the ability to infer causality or track the evolution of configurations over time. Finally, while fsQCA excels at identifying sufficient conditions and equifinality, interpreting the precise nature of the interactions within complex configurations requires theoretical grounding and is subject to interpretive nuances.

Future research should address these limitations. Collecting more granular, firm-level data directly on social enterprises, their adoption and use of specific deep technologies, and their contribution to objectively measured regenerative outcomes is crucial. Longitudinal studies are needed to understand how configurations of factors change over time and how they influence the scaling trajectory and long-term regenerative impact of social ventures. Qualitative case studies could provide rich, in-depth insights into the specific mechanisms through which deep technologies are adopted and leveraged within particular configurations to achieve regenerative outcomes, exploring the interplay of individual mindsets, organizational practices, technology characteristics, and contextual dynamics. Developing standardized, internationally comparable measures for regenerative outcomes and deep tech adoption in the social sector would significantly enhance future research capabilities.

5. Conclusion

This study explored the complex interplay of technological, individual, organizational, and contextual factors associated with tech-driven regenerative scaling potential in social entrepreneurship using a configurational fs/QCA approach. The findings highlight that high levels of early-stage entrepreneurial activity and the formalization of ventures, serving as proxies for scaling potential, are not driven by single factors but by diverse combinations of conditions. Prominent conditions across different pathways include high perceived capabilities and opportunities among entrepreneurs, as well as aspects of the enabling environment such as new business density and, in some configurations, innovation and ESG commitment.

The theoretical contribution lies in applying a configurational perspective informed by Theories of Technological Change and Diffusion and Causal Layered Analysis to this emerging area. This approach reveals the equifinal nature of scaling potential and underscores that achieving regenerative impact likely depends not just on applying technology (Systemic level) but on doing so within contexts and with mindsets aligned with regenerative worldviews (Worldview/Myth layers). Practically, the study offers a framework for social entrepreneurs, investors, policymakers, and tech developers to understand the complex landscape of tech-enabled scaling potential, guiding strategy, investment decisions, policy design, and technology development towards fostering a more regenerative economy through social innovation. The intersection of deep technology and regenerative social entrepreneurship holds immense potential, the realization of which depends on cultivating the right combinations of conditions.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org**.**

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Data Availability Statement: The raw data analyzed in this study were obtained by the author from publicly available sources:

1. Entrepreneurship data can be found on the World Bank website: https://www.worldbank.org/en/programs/entrepreneurship
2. GEM data can be found on the GEM Consortium website: https://www.gemconsortium.org/data/key-aps
   Access to these original data sources does not require a subscription.

The processed data and analytical code (fsQCA software version 4.1 for data manipulation/calibration) generated during the current study are available from the corresponding author upon reasonable request. They will be deposited in the journal's repository upon publication. Permanent access details [e.g., DOI or specific URL] will be provided at that time.

Abbreviations

AI: Artificial Intelligence

CLA: Causal Layered Analysis

EGCC: Environmental, Social, and Governance Commitment & Consciousness

FFR: Fear of Failure Rate

Fs/QCA: Fuzzy-Set Qualitative Comparative Analysis

GEM: Global Entrepreneurship Monitor

High_E_TEA: High Total Early-Stage Entrepreneurial Activity

IoT: Internet of Things

LLC: Limited Liability Company

Num_Entrepreneur_LLC: Number of Entrepreneurs Forming Limited Liability Companies

PC: Perceived Capability

PO: Perceived Opportunity

SE: Social Entrepreneurship

SDGs: Sustainable Development Goals

high_SSE: High Social Status Entrepreneurship

TEA: Total Early-Stage Entrepreneurial Activity

WB: World Bank

new_BDR: New Business Density Rate

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