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AI-Driven Process Innovation: Transforming Service Start-Ups in the Digital Age

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Abstract

In today's fast-moving digital economy, service start-ups are reshaping industries; however, they face intense uncertainty, limited resources, and fierce competition. This study introduces an Artificial Intelligence (AI)-powered process modeling framework designed to give these ventures a competitive edge by combining big data analytics, machine learning, and Business Process Model and Notation (BPMN). While past models often overlook the dynamic, human-centered nature of service businesses, this research fills that gap by integrating AI-Driven Ideation, AI-Augmented Content, and AI-Enabled Personalization to fuel innovation, agility, and customer-centricity. Expert insights, gathered through a two-stage fuzzy Delphi method and validated using DEMATEL, reveal how AI can transform start-up processes by offering real-time feedback, predictive risk management, and smart customization. This model does more than optimize operations; it empowers start-ups to thrive in volatile, data-rich environments, improving strategic decision-making and even health and safety governance. By blending cutting-edge AI tools with process innovation, this research contributes a fresh, scalable framework for digital-age entrepreneurship. It opens exciting new pathways for start-up founders, investors, and policymakers looking to harness AI's full potential in transforming how new ventures operate, compete, and grow.

Keywords: artificial intelligence; start-ups; big data analytics; business process modeling; BPMN; predictive analytics; service innovation; entrepreneurial decision-making

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1. Introduction

Entrepreneurship is broadly defined as "any effort made by individuals to start a business and self-employment" [1]. Over the past decade, scholarly attention at the intersection of entrepreneurship and start-up dynamics has increased significantly [2,3]. Gaio et al. [2] characterize a start-up as a human-centered institution committed to delivering novel services, considering high uncertainty with both its innovative potential and inherent vulnerability.

In light of the increasing levels of complexity and ambiguity faced by service start-ups, this research contributes a framework for visualizing processes via AI. The modeling framework employs various methods of big data analysis and machine learning in strategic and operational decision-making within this context. The proposed AI-supported framework employs other AI methods, namely natural language processing (NLP) and predictive analytics, which are supposed to enhance operational agility and the governance of strategic decision-making (an element that may make agile start-ups more successful), including health and safety in services-based ventures. In services, entrepreneurship is often perceived more as stand-alone businesses that operate outside established organizational structures. AI-Driven Ideation helps service start-ups rapidly brainstorm through sentiment analysis with natural language processing. AI-Augmented Content helps service start-ups engage in machine learning to pull out insights based on customer feedback and operations data, and AI-Enabled Personalization supports service start-ups in using predictive analytics to personalize services in-the-minute. Each of these elements can be included in the BPMN model to signify the iterative, customer-centric nature of operational decision-making.

Typically, these organizations tend to follow a decentralized approach like franchising or contracting, which allows them flexibility and makes use of their already available institutional capabilities [4,5] While they frame up more flexibility, they still entail significant strategic and operational challenges. While they have a growing global presence and importance in the economy, start-ups still have a high failure rate. Entrepreneurs face many challenges before they identify sustainable innovation, or even good business models [6]. While technical problems and structural mismatch can be considered well-known early-stage failure types, people problems like team-building, learning for the organization, and knowledge diffusion are considered under-researched types of failure [7,8]. Ultimately, although they are unfortunate, entrepreneurial failure can be leveraged for experiential learning and to promote subsequent opportunity [9].

OECD countries have prioritized start-ups as key contributors to job creation, innovation, and long-term economic resilience, and investments in the startup allocation accounted for nearly 40% of all entrepreneurial funding [10]. The COVID-19 pandemic created disturbances never seen before, which shone a light on structural weaknesses and accelerated the conversation around adaptive, tech-enabled approaches. In this context, researchers have become increasingly focused on reducing failure rates and shortening time-to-market via data-driven approaches [11], especially those utilizing artificial intelligence (AI), machine learning, and big data analytics.

Within this evolving landscape, the process-based perspective offers a valuable framework for understanding the progression of start-up activities. Rooted in foundational process theories [12,13], this approach conceptualizes entrepreneurship as a dynamic, context-sensitive phenomenon shaped by iterative decision-making and organizational intent. Seminal models developed by [14–16] have significantly contributed to defining the stages of entrepreneurial development. Later, Ahmadpour Dariani [17] expanded upon these frameworks to address the complexities of 21st-century start-up ecosystems. However, most of these models did not fully incorporate emerging technologies, such as blockchain, AI, and real-time data streams that are now central to modern entrepreneurial practice [18].

Addressing this gap, the present study proposes an AI-augmented process model specifically designed for service-oriented start-ups. Developed through a qualitative methodology grounded in subjectivist epistemology, the model leverages large-scale, unstructured data and integrates insights from big data analytics and machine learning. Expert consensus was achieved using a two-round fuzzy Delphi method, while causal relationships among model components were analyzed through the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique.

This model incorporates the nuances of start-up ecosystems, as well as the necessity for human judgment, learning, and adaptive capability while providing a structured but flexible framework for entrepreneurship decision-making through the inclusion of AI tools—including natural language processing for customer sentiment analysis, and predictive modeling for risk mitigation. The framework also considered worker health and safety and the resilience of organizations as part of strategic planning, allowing it to be used as part of the entrepreneurial decision-making framework for sustainable development of the start-up.

This research contributes to an academic and practical space in developing a scalable roadmap for intelligent entrepreneurship; the research contributes to academia and the practical application of a scalable framework to help support the entrepreneurial process in a digital world. It also provides a pathway for those who wish to undergo further research and practical applications within varied service sectors operating in conditions of uncertainty.

2. Literature Review

2.1. Entrepreneurship

Entrepreneurship, derived from the French term entreprenerd, meaning "to undertake," has evolved significantly from its early roots, originally referring to organizers of cultural events, into a globally recognized engine of economic transformation [11,19]. Modern interpretations converge on the idea of entrepreneurs as individuals who initiate, organize, manage, and assume the risks of new ventures, often under conditions of uncertainty [20]. Ref. [20] discussed distinction between entrepreneurs and managers emphasized the central role of risk-taking in entrepreneurial activity, a concept that remains highly relevant today.

Traditionally, entrepreneurship has been viewed as a dynamic process that turns creative ideas into productive economic and social output. Regardless, in the relatively short time since the digital age arrived, the nature of entrepreneurship is challenging to pin down; it connects with unwavering clarity the continuously evolving forces of artificial intelligence (AI), machine learning (ML), and big data analytics in the broader entrepreneurial realm. Presently, these innovations are more than platforms for automation; they are redesigning the process of opportunity discovery, venture development, and market engagement as part of the entrepreneurial process. The current entrepreneur is becoming more and more a data-driven decision-maker who is relying on algorithms to create a competitive advantage, improve operational capacities, and predict market activity with more accuracy than in the past.

Entrepreneurship is still mainly about innovation, but the processes are now being mediated considerably by digital intelligence. Entrepreneurs are no longer completely reliant on intuition or standard market research. They are using predictive analytics, real-time sentiment analysis, and automated trend forecasting, all of which allow for rapid, ongoing iterations of emerging business models [21]. AI can provide pattern recognition across very large datasets, revealing interpretations for product development, marketing approaches, and risk management. This process not only reduces time-to-market but can (in many known instances) create more resilient and scalable start-ups.

Entrepreneurship has been defined in the literature as the process of creating something new and with value through the expenditure of time and resources while dealing with financial, psychological, and social uncertainty and risk [22]. This definition is useful for today's context in a digital world in that entrepreneurs also need to deal with data privacy risks, algorithmic bias, and ethical considerations surrounding automated decision-making. The entrepreneurial journey in a digital context demands that the entrepreneur be competent in data governance, technological literacy, and AI ethics, including areas of knowledge upon which sustained innovation in an interconnected world increasingly depends.

Ref. [12] discussed understanding of entrepreneurs as facilitators of the "creative destruction", the process that demolishes existing market paradigms to facilitate new patterns of commerce, has never been more significant. Practicing entrepreneurs continue to disrupt existing industries, create new markets, and innovate economic systems using emerging technologies. Entrepreneurs are now digital agents of change using emerging technologies associated with blockchain, the Internet of Things (IoT), and AI to spur fundamental system-wide innovation and economic regeneration [12,23,24].

Furthermore, big data has expanded the potential of entrepreneurship to generate economic and social value. For example, using unstructured and big datasets, entrepreneurs can identify unaddressed markets, tailor offerings, and measure impact with incredible resolution. This kind of ability becomes immense leverage within smart cities and digitally intense economies, where entrepreneurship can foster resilient local economic capacity, increase competitive multiplicity (or diversity), and allow for micro-targeted service innovation [25,26].

Entrepreneurship is important for knowledge spillovers and technology diffusion, both of which can now occur quickly thanks to AI's ability to learn from diverse, large-scale sources of data. These spillovers are important for macroeconomic conditions as well as human developments through new digital jobs, remote entrepreneurship, and access to education and healthcare services [27,28].

From a social economic standpoint, entrepreneurship is playing a major role in the flow of government revenues from technology licensing and taxes on the digital commerce economy, as well as government incentives aimed at innovative businesses [29]. Governments essentially use the revenues for improving infrastructure, paying for education, healthcare, and R&D investments, which extends the innovative development cycle [30].

In conclusion, entrepreneurship is now intimately linked with AI and big data, having transitioned from something focused on an individual to a technology-based system-level innovation driver for change in society. In this respect, future research and practice should increasingly take up data-driven approaches to better articulate and inform the emergent functions of entrepreneurship operating in a digital economy.

2.2. Start-Up

Start-ups have become a global phenomenon, attracting significant attention due to their potential to drive transformative change, particularly in the field of information technology (IT). For instance, companies like Google and Facebook, which permeate daily life today, were small, university-based start-ups at their inception. They rose from students' dorm rooms and garages to global corporate economic power in a relatively short time; nowadays, they represent models of success for young, creative entrepreneurs [10,11]. The various success stories, particularly those from Silicon Valley, have intrigued the public and also highlighted the economic strategic importance of being able to become a start-up.

Beyond individual success, start-ups have profound economic implications. According to Schiessl et al. [31], the IT sector has outpaced traditional economic pillars, such as mining, public services, and agriculture, in driving global innovation and growth. In countries like the United States, tech-driven start-ups are leading the transition toward a knowledge-based economy that prioritizes agility, scalability, and innovation over resource dependence.

The creation of business growth centers and incubators in the 1950s marked the beginning of institutional support for start-ups. These early support programs provided comprehensive service components such as technical added value, financial robustness, mentoring, and a place for transforming ideas into viable business concepts. Culturally, incubators were national-level entities for the purpose of economic development, related to the potential of market capitalization and investment in innovative ideas and insight [32,33]. Evidence has determined the relative increase in success rates (lower cost of operation, greater financial metrics) for start-ups or business ideas enabled and/or nurtured through the incubator experience [34,35].

Advancing this notion, the mid-2000s saw a new set of start-up support mechanisms in the form of accelerators. Whereas incubators are often ridden with ambiguity, accelerators work with a structured timeline and are explicitly defined by five characteristics: (1) competitive selection process, (2) they take an equity stake in exchange for seed investment, (3) a focus on small, agile teams opposed to individual founders, (4) intensive mentorship and structured programming, and (5) cohort-based learning [34]. Y Combinator was launched in 2005, serving as a catalyst for the explosion of similar programs in the U.S. and Europe at exponential rates. Many accelerators have produced companies of significant value.

Despite the growing ecosystem and heightened political interest, academic research into start-up development remains relatively underdeveloped [36]. Nonetheless, available evidence suggests that accelerator programs have a positive impact on entrepreneurial outcomes, including enhancing learning, expanding networks, and improving venture quality [5].

Start-ups are increasingly recognized as engines of economic dynamism, challenging legacy corporations across sectors. High-growth start-ups, often referred to as "entrepreneurial ventures," emphasize scalable and repeatable business models [8]. Unlike traditional business investments, start-up financing involves high levels of risk and uncertain returns. Venture capitalists, angel investors, and institutions such as business growth centers typically offer not only financial backing but also strategic support in the form of mentorship, operational guidance, and market insights [37]. Their selective investment strategies are designed to mitigate risk and maximize long-term portfolio returns.

Today, entrepreneurial financing extends well beyond personal savings to include venture capital, angel investment, and structured incubation programs [21]. This multi-stakeholder approach is reshaping how start-ups access capital and scale their operations, contributing to a more resilient and innovation-driven economy.

2.3. Start-Ups in the Era of AI and Big Data

Start-ups have transitioned from being relatively young and newly established to being well developed, now representing a complete ecosystem that provides technical support, strategic business consulting, financing, and opportunities to access networks [32]. These incubators can contain many different types of undertakings with multiple possible scales. However, it remains to be seen if entrepreneurs, investors, or governments will focus on developing start-ups toward industry-shaping businesses or fixing broken, inefficient, or high-cost businesses. Shortly after the outbreak of COVID-19 and during the pandemic itself, there was a strong pivot toward innovation and start-ups appearing in many existing industries, such as healthcare, hospitality, and transportation. Digital convergence gave consumers and businesses the tools to rapidly and easily adapt to a new circumstance that otherwise could not exist. As new technologies and business models emerge, there is no doubt that opportunities for new start-ups will arise, whether for ultimate businesses that provide new growth or mature organizations providing opportunities. It should also be understood in this service sector; the future may also lie in using service robots. While robots are evaluated in hospitals at various levels for efficiency, the analysis of using robots at various contact points is marked by failure: how many hospital personnel can a robot successfully replace? It is unrealistic to believe that a new entrepreneur can create a business that eliminates hospital staff. The focus of this chapter will be on professional activities that are now using more innovators, entrepreneurs, and start-ups to solve problems or explore opportunities. For example, some academic professionals use green economics or social accountability in their solutions while seeking start-up companies that must live and die within the basic parameters. Technology has been captivating the attention of the public, private sector, and investment companies. New technology is considered an important factor in shaping the future of public relations, large public organizations, and non-profit organizations along similar lines. From entertainment, news media, or the use of robots to help solve the impact of pandemic closures or technology use when auto factories, or other service sector industries, became non-contact or virtual, the use of technology has had a dramatic social effect. According to Gaio, Clibborn, and Schiessl, there are few examples of how new businesses have evolved rapidly to favor consumers and organizations. The remainder of this chapter will address how some of the larger industries and sectors of the economy in Canada used large applications of technology to initiate or start new opportunities (within the parameters of public and investment guidelines). These large industries would comprise oil and gas, retail, healthcare, and transportation, to name but a few. Despite academic and positive research acknowledging that new technology brings both positive and negative impacts for organizations across Canada, it remains an area ripe for future opportunities. This chapter will also identify early adopters of entrepreneurs and small businesses from outcomes of these organizations across Canada (public and private), starting another shift to public and non-profit organizations preparing to use technology to stimulate/start new activities at their own institutions. To hopefully create some relationships with respect to future research activities, the conclusion will quickly review some references related to public and non-profit organizations that are using technology to displace their residual corporate thinking to prepare for change. By willingly focusing their funding, they can either save public spaces from taxes and service delivery costs. Most of the social changes noted in this chapter would be an acceptable outcome for used technology to not "go with the flow or accept status quo" outcomes.

Following on from the foundational work of incubators, start-up accelerators began to be widely used in the mid-2000s as a more focused, performance-oriented model. The launch of Y Combinator marked the beginning of a redefined look at start-up development with their use of a data-based, cohort-based approach that not only included seed funding (in exchange for equity), but intensive mentorship hours and structured, short-time programming. Typically, accelerators have: (1) a highly selective admissions process, (2) an equity investment relationship, (3) collaborative teams of peers, (4) structured and time-limited programming, and (5) peer learning through cohorts [34].

An increasing number of accelerators and incubators are beginning to utilize artificial intelligence (AI) and big data technologies to optimize entrepreneurial success. AI tools are enabling instant performance statistics, personalized mentoring, and predictive modeling of prospective start-up feasibility that accounts for customer behavior, market trends, and engagement with the product. These tools enable investors to manage risk while also providing entrepreneurs and funding institutions with further strategic options.

Despite approaching more inherent institutional infrastructures, academic research has only recently considered formalizing evidence toward the study of start-up success in data-rich contexts [36], as well as the amount of growth that has happened associated with accelerator-led programs—especially over the course of the past few years and especially throughout the U.S. and Europe, where both have shown significant potential for programs to implement learning and enhance the coding of entrepreneurial skills whilst building supportive extended network ties that cascade to benefit long term sustainable outcomes [5].

Start-ups are increasingly viewed not merely as economic participants but as engines of digital and data-driven innovation. Unlike traditional businesses, which emphasize gradual, linear growth, start-ups pursue scalable, repeatable models designed for rapid expansion through technology. In this high-risk, high-reward environment, entrepreneurial investors, including venture capitalists, angel investors, and corporate accelerators, could play an active role not only in financing but also in shaping the strategic and operational trajectories of ventures [8].

These investors are adopting AI-driven due diligence practices, using machine learning algorithms to assess team capabilities, product/market fit, and broader market dynamics. Real-time performance monitoring through interactive dashboards enables agile decision-making and portfolio optimization [37]. As a result, investment strategies are becoming increasingly data-intensive, allowing for improved risk management and higher success rates across start-up ecosystems.

In conclusion, today's start-ups operate within a digitally enhanced entrepreneurial landscape, where technological fluency, data literacy, and agile execution are as essential as vision and creativity. The convergence of AI, big data, and entrepreneurial energy is redefining how businesses are launched, scaled, and sustained, and it is ushering in a new era of intelligent entrepreneurship.

2.4. Business Processes in the Intelligent Enterprise Era

The concept of "process" has long been recognized as fundamental to organizational functioning and strategic execution. Merriam-Webster defines a process as a "continuous and progressive sequence of actions or changes that occur in a relatively predictable manner to produce a specific outcome" [38]. In both natural and engineered contexts, processes are structured and intentional sequences of activities designed to achieve defined results. Within business environments, processes serve as frameworks that integrate people, technology, and resources to generate value for internal or external stakeholders [39].

In the era of intelligent enterprises, AI-Driven Ideation, AI-Augmented Content, and AI-enabled personalization play crucial roles in enhancing business process modeling. AI-Driven Ideation leverages mind mapping and creative insights to generate innovative ideas for process improvements. AI-Augmented Content enhances Business Process Model and Notation (BPMN) with insights from large-scale, unstructured data sources. AI-enabled personalization applies predictive personalization and real-time insights to tailor processes to customer needs. These AI methodologies, including NLP for real-time analysis of customer feedback and predictive analytics for early risk identification, provide a structured yet adaptable guide for entrepreneurial decision-making.

At its core, every business process functions as a transformation mechanism, converting inputs—such as information, labor, capital, and materials- into outputs that meet organizational or customer needs. As digital technologies increasingly permeate organizational life, enterprises now design, manage, and optimize these processes using advanced tools to enhance efficiency, traceability, adaptability, and strategic alignment.

Bitkowsk [40] defines a business process as "a set of actions that an entrepreneur undertakes to deliver a product or service." These actions may occur within a single department or span multiple functional units. Processes that cut across departments are considered cross-functional. Those delivering outputs to external clients are classified as primary processes, while those supporting internal operations are categorized as support processes. This classification allows organizations to prioritize process improvements based on strategic value and stakeholder impact.

In the last two decades, Business Process Management (BPM) has changed considerably. BPM is no longer just about efficiency and cost savings. It has become a key element of digital transformation strategies. It offers a complete set of methods for discovering, modeling, analyzing, executing, and continuously improving business processes to achieve agility in complex and dynamic environments [41].

Recent developments have integrated BPM with transformative technologies, notably artificial intelligence (AI), robotic process automation (RPA), and big data analytics. AI-enhanced BPM systems now enable organizations to detect inefficiencies, predict bottlenecks, and autonomously recommend or execute corrective actions. Machine learning algorithms analyze both historical trends and real-time performance metrics to support continuous process optimization, thereby improving organizational responsiveness and resilience.

A central pillar of BPM is business process modeling that includes the visual and analytical representation of workflows and decision pathways. More than a descriptive tool, process modeling supports strategic foresight by simulating future-state processes, incorporating stakeholder feedback, and guiding digital transformation [42,43]. These models serve as blueprints for automation, systems integration, customer experience design, and cross-functional collaboration.

Among available methodologies, Business Process Model and Notation (BPMN) has emerged as the global standard for process modeling. Its strength lies in offering a shared visual language that bridges technical and managerial domains. BPMN's intuitive yet rigorous structure makes it accessible to business analysts while remaining technically robust for IT implementation. As organizations increasingly pursue process digitization and automation, BPMN has seen widespread global adoption, including in Iran, where both international and domestically developed Business Process Management Systems (BPMS) incorporate it for intelligent workflow design.

To inform the development of a robust process model tailored to service-based start-ups, a systematic review of 22 peer-reviewed studies was conducted. From this analysis, eight high-impact models, recognized for their empirical grounding and practical applicability, were selected for deeper evaluation (see Table 1). These models were assessed based on their adaptability to dynamic start-up contexts, scalability, ease of integration with intelligent systems, and compatibility with AI-driven data inputs.

Table 1. Process model design techniques in research.

Row	Writer	RAD	Flowchart	DFD	EPC	Petri Net	IDEF	BPMN	UML
1	Vera & Zapata (2022) [41]		*	*		*	*	*	*
2	Huang et al. (2022) [5]		*	*	*	*	*	*	*
3	Amorós et al. (2021) [25]		*	*		*	*	*	*
4	Sparx Systems & Stephen Maguire (2020) [44]		*	*				*	*
5	Pearson (2018) [45]		*	*		*	*	*	*
6	Pereira & Silva (2016) [46]	*			*		*	*	*
7	Tangkawarow & Waworuntu (2016) [47]			*			*	*	*
8	Nagm-Aldeen et al. (2015) [48]	*	*	*		*	*		*

Table 1. *Cont.*

Row	Writer	RAD	Flowchart	DFD	EPC	Petri Net	IDEF	BPMN	UML
9	Geyer et al. (2015) [49]				*			*	*
10	Rima et al. (2013) [50]			*	*	*	*	*	*
11	Johansson et al. (2012) [51]		*		*	*		*	*
12	Chand & Chircu (2012) [52]	*	*	*	*		*	*	*
13	Heidari et al. (2013) [53]	*			*		*	*	*
14	Aldin & de Cesare (2009) [54]		*	*	*	*	*	*	*
15	Recker (2006) [55]		*	*	*	*	*	*	*
16	Aldin & De Cesare (2011) [56]	*	*	*		*		*	
17	Damij (2007) [57]		*	*		*	*		*
18	Ziemann et al. (2007) [58]				*	*		*	*
19	List & Korherr (2006) [59]	*			*	*	*	*	*
20	Giaglis (2001) [60]	*	*	*		*	*		*

Note: * indicates that the corresponding modeling technique was used or referenced in the cited study.

In conclusion, business processes are no longer static or linear routines; they are dynamic, data-informed systems that continuously evolve in response to internal insights and external signals. Modern BPM and process modeling practices, empowered by AI and digital infrastructure, are essential tools for navigating complexity, driving innovation, and sustaining long-term competitive advantage. They are especially critical in start-up environments, where agility, speed, and intelligent decision-making are key to achieving sustainable success.

Based on a comprehensive review of 22 foundational studies in the domain of business process modeling, Table 1 presents the frequency and prominence of eight major modeling techniques. Among these, Unified Modeling Language (UML), Business Process Model and Notation (BPMN), IDEF, and Petri Nets were identified as the most frequently cited approaches, reflecting both theoretical robustness and practical utility across academic and professional contexts.

Of these, BPMN emerged as the most contemporary, adaptable, and contextually suitable technique for modeling dynamic, service-oriented start-up environments. Its core strength lies in its ability to bridge communication between business and technical stakeholders through a standardized and intuitive visual language. This dual accessibility makes BPMN particularly valuable in early-stage ventures, where multidisciplinary collaboration and rapid iteration are essential. Based on both its frequency in the literature and expert consultations conducted during this study, BPMN was selected as the foundational modeling framework.

Given the relative novelty and underdevelopment of structured process research specific to service start-ups, it was essential to analyze existing models to avoid redundancy and build upon validated conceptual frameworks. However, the literature indicates a persistent gap: most existing models are either highly generalized or geared toward product-centric enterprises, offering limited applicability to service-driven ventures. To address this deficiency, the present study contributes by refining and adapting process elements specifically tailored to service-based start-ups.

To develop a robust and contextually relevant BPMN-based model, key process parameters were extracted from prior studies and systematically categorized. Parameters explicitly tied to physical goods, such as inventory management, warehousing, or distribution logistics, were excluded. Those with overlapping relevance, such as "product development" or "market launch," were reinterpreted through a service-oriented lens. Additionally, parameters unique to service ventures, such as service ideation, value co-creation, and intangible delivery mechanisms, were emphasized to reflect the operational and experiential distinctiveness of service start-ups.

Foundational contributions by [61] highlighted the critical early-stage components of venture formation, particularly relevant to service sectors. These include opportunity recognition, risk management, team building, competitive intelligence, and the establishment of legal, financial, and strategic structures. Further refinement by [62] expanded this framework, emphasizing the non-linear, iterative, and adaptive nature of entrepreneurial processes, which is especially vital in service contexts, where continuous customer engagement and responsiveness are key to value creation.

A recurring theme in the recent literature is the underrepresentation of human-centered and behavioral dimensions in traditional process models. Scholars [5,25,32,40] argue for the integration of soft variables, such as team motivation, cognitive flexibility, individual agency, and cultural adaptability, particularly within volatile, innovation-intensive start-up environments. These dimensions are essential to understanding how entrepreneurial teams navigate uncertainty, respond to feedback, and sustain innovation over time.

Vera and Zapata [41] offer a contemporary systems-oriented perspective by conceptualizing service start-ups as socio-technical systems. This view positions start-ups not merely as economic entities, but as dynamic ecosystems where technical infrastructures and social behaviors co-evolve. From this vantage point, service start-ups act as agents of broader socio-technical transformation by facilitating adaptive learning, participatory innovation, and systems-level change.

Building on this insight, the present study adopts a systems thinking approach, recognizing that any viable model for service start-ups must integrate both technological intelligence and human insight. The BPMN-based framework developed here is designed to reflect this interaction, providing a flexible, scalable, and intelligent process modeling tool capable of visualizing, analyzing, and optimizing service start-up operations in complex, AI-enhanced, and data-rich environments.

2.5. Research Innovation

Given the diversity and complexity of entrepreneurial environments, there is no single model capable of representing new venture creation and encompassing the full range of variables relevant to starting up. While there are several integrated frameworks to unite and summarize the common characteristics of previous models, they are often too generalized, collectively bringing together too many elements and variables at the same time (e.g., opportunity recognition, strategic shaping, team formation, implementation) and failing to contextualize these attributes in a particular sector or entrepreneurial context.

The integrated frameworks strive to capture the whole of entrepreneurial activity by collating variables and stages that were yielded from the previous literature. However, a continual limitation of these frameworks is their lack of specificity; the variables they contingently categorize are broad and often poorly defined, operationally or otherwise, making them impractical for analyzing and describing new ventures. Therefore, they do not often provide particularly useful information or advice for specific start-up situations, especially in niche areas of entrepreneurship such as service-providing entrepreneurship

A more realistic and potentially fruitful approach for both scholarly inquiry and practical engagement is to undertake sector-specific and context-specific process models. This is especially relevant for nascent ventures that work with a level of resource constraint, a high degree of uncertainty, and/or account for sector-specific expectations.

To satisfy this need, the current study proposes developing a specific process model for workers' health and safety in service start-ups. This is motivated through the specific nature of service enterprises, where human interaction, intangible value delivery, and "fluid" work environments are in focus. By limiting the frame of reference back down to this very important but lesser-studied complexity, it is anticipated that this model could provide a more realistic, practical, and sector-relevant process model that considers not only strategic and operational processes, but also important human considerations.

Ultimately, this work seeks to contribute to a new generation of start-up process models that can be meaningfully connected to theory and can be implemented in practice, providing actionable insight for founders, practitioners, and policymakers wanting to develop resilience, employee well-being, and sustainability in service-based start-ups.

3. Research Method

Despite extensive scholarly efforts, there remains no universally accepted or fully comprehensive model that encapsulates the complete process of new venture creation, particularly within the diverse and evolving landscape of service-oriented start-ups. While several integrated frameworks have been proposed to address this gap, they often attempt to aggregate a wide range of variables and features from earlier models without offering sufficient specificity or operational clarity. These general models, though useful in broad conceptual terms, frequently lack the granularity required to address the nuanced challenges and sector-specific demands faced by start-up founders.

The limitations of these theoretical frameworks highlight the need for more context-sensitive and application-driven models, especially those tailored to specific domains within the entrepreneurial ecosystem. A key shortcoming of the existing literature is the lack of targeted focus on critical areas such as workers' health and safety, a vital yet often overlooked aspect in the design and operation of service-based start-ups.

To address this gap, the present study proposes the development of a sector-specific, process-oriented model that integrates expert insights with advanced methodologies, including BPMN, AI-driven process analysis, and socio-technical systems thinking. The focus is on designing a model that supports health and safety practices for workers within service start-ups, an area with significant implications for operational sustainability, legal compliance, and human capital management.

By incorporating parameters derived from empirical research, expert consensus (via the fuzzy Delphi method), and systems-level analysis (via DEMATEL), this study aims to contribute an actionable and realistic framework aligned with the unique characteristics of service start-ups. This approach not only enhances practical relevance but also opens new pathways for academic inquiry, offering a foundation for further refinement and cross-sector adaptation of the proposed model.

In doing so, the study advances current process theory by shifting from generalized abstraction to targeted innovation, creating tools that are not only theoretically sound but also technologically enabled and practically implementable.

AI-Driven Process Modeling Framework

The AI-driven process modeling framework is built on three core components: Core attributes of AI-Driven Ideation, AI-Augmented Content, and AI-Enabled Personalization (Figure 1). AI-Driven Ideation leverages mind mapping and creative insights to generate innovative ideas, while AI-Augmented Content enhances BPMN with data-driven insights. AI-Enabled Personalization applies predictive personalization and real-time insights to tailor processes to customer needs [63]. Developed iteratively based on expert input, the proposed framework functions as a robust, that blends into the comprehensive AI integration, covering advanced techniques from big data analytics and machine learning to enhance strategic and operational decision-making, providing a robust, intelligent system for improving operational agility, strategic decision-making, and health and safety governance in service-oriented start-ups. Moreover, as shown in Figure 1, the framework is developed in three AI capabilities. AI-Driven Ideation supports creative exploration through data-informed brainstorming. AI-Augmented Content enhances the process modeling by integrating real-time insights from unstructured data. AI-Enabled Personalization ensures that service delivery is tailored to user needs through predictive analytics. Together, these elements form a cohesive system that supports agile, customer-centric innovation in service start-ups.

Figure 1. AI-driven process modeling framework for service start-ups.

4. Findings

The findings of this study begin with an analysis of the expert participants involved in the development and validation of the proposed process model for service start-ups. The target population consisted of specialists in entrepreneurship, start-up ecosystems, and Business Process Model and Notation (BPMN) techniques. To understand the demographic distribution of the participants, descriptive statistical measures were applied across variables such as age, education level, work experience, and professional role.

The data showed that 75% of the participants (15 out of 20) were aged between 25 and 35. Age was used as a demographic indicator to show how many younger professionals are becoming involved in emerging areas in which "BPM"-driven process modeling and start-ups represent a small business strategy. In any event, it is not surprising that younger generations would dominate in areas such as BPMN and start-ups, especially considering their aversion to resistive technology and entrepreneurial risk, versus older professionals who likely would not have the same engagement based on their career choices or commitment to support digital transformation options.

In order to assess the strength of the research instrument, the internal consistency of the expert questionnaire was assessed with Cronbach's alpha. In the first data collection round, the alpha was calculated at 0.51, falling below the overall acceptable reliability threshold of 0.70, and there was a need for refinement.

A deeper analysis of individual questionnaire items revealed that the question, related to voluntary withdrawal from a previous company, had a negative impact on the reliability score. Several expert insights explained the lack of relevance of this item in the context of modern start-up formation:

1. Many founders are not necessarily transitioning from traditional employment.
2. For some, the start-up represents a parallel endeavor rather than a complete career shift.
3. In certain cases, start-ups are launched within existing organizational structures, eliminating the need for a formal job exit.

Through the feedback process, we removed the item, and the modified model—and a modified version of the questionnaire—was sent to the expert group. This is consistent with agile, data-informed research, which emphasizes iterative refinement based on stakeholder feedback. In the second round of analysis, the modified questionnaire had an acceptable reliability and improved internal consistency with a Cronbach's alpha of 0.74. This suggested that the revised parameters were more consistent with the experts' understanding of, and the realities of, the sector in which the experts/participants operated for their own applications.

Following this validation, the process model was updated to reflect the refined parameter set and restructured accordingly to address the specific needs of workers' health and safety in service start-ups. The revised model is both theoretically sound and practically actionable, developed through iterative expert engagement and grounded in the integration of AI-informed process thinking and socio-technical systems design (Refer to Table 2 for a detailed list of final model parameters and the redesigned process structure).

To quantify and visualize these interrelationships, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique was applied. This method is particularly well-suited for complex, interdependent systems such as service start-ups, where dynamic interactions between organizational, strategic, and human factors are critical. DEMATEL enabled the identification of causal and dependent relationships among model components, offering clarity on which parameters act as key influencers, and which are primarily reactive within the process structure.

Table 2. The final parameters of the process model for service start-ups.

Row	Sub-Process	Van de Ven & Poole (1989) [64]	Vesper (1990) [16]	Gartner and Katz (1988) [14]	Bierley (1985) [65]	Gartner (1985) [61]	Larson and Star (1993) [66]	Veciana (1988) [67]	Deakins & West Ham (2000) [62]	Bohács et al. (2016) [68]	Pearson (2018) [45]	Diamond (2019) [38]	Bitkowsk, (2020) [40]	Amorós et al. (2021) [17]	Doellgast & Wagner (2022) [32]	Vera & Zapata (2022) [41]	Zhao et al. (2024) [35]
1	Intending to create a startup			*	*			*			*	*					
2	Creative idea generation and choosing the best idea	*	*						*			*	*		*	*	
3	Discover and recognize opportunities					*	*	*	*								
4	Market research, analysis, and needs assessment		*			*		*	*				*	*			
5	Recognize competitors					*											
6	Risk assessment and rational risk acceptance					*			*								
7	Participate with a team with appropriate background and knowledge, and role determination		*		*	*	*	*	*		*	*			*	*	

Table 2. *Cont.*

Row	Sub-Process	Van de Ven & Poole (1989) [64]	Vesper (1990) [16]	Gartner and Katz (1988) [14]	Bierley (1985) [65]	Gartner (1985) [61]	Larson and Star (1993) [66]	Veciana (1988) [67]	Deakins & West Ham (2000) [62]	Bohács et al. (2016) [68]	Pearson (2018) [45]	Diamond (2019) [38]	Bitkowsk, (2020) [40]	Amorós et al. (2021) [17]	Doellgast & Wagner (2022) [32]	Vera & Zapata (2022) [41]	Zhao et al. (2024) [35]
8	Planning and drawing a business plan							*	*								
9	Provide a minimum acceptable product and pilot test								*			*	*				
10	Collaborate with incubators (accelerators)							*									
11	Collecting resources from suppliers		*	*	*	*	*	*						*	*	*	
12	Develop and launch a service	*				*	*	*	*								
13	Establish a legal, financial, and contractual structure				*	*	*		*			*	*	*			
14	Achieve the first sale	*	*	*	*	*											
15	Create and sell next services and grow	*		*		*											

Table 2. *Cont.*

Row	Sub-Process	Van de Ven & Poole (1989) [64]	Vesper (1990) [16]	Gartner and Katz (1988) [14]	Bierley (1985) [65]	Gartner (1985) [61]	Larson and Star (1993) [66]	Veciana (1988) [67]	Deakins & West Ham (2000) [62]	Bohács et al. (2016) [68]	Pearson (2018) [45]	Diamond (2019) [38]	Bitkowsk, (2020) [40]	Amorós et al. (2021) [17]	Doellgast & Wagner (2022) [32]	Vera & Zapata (2022) [41]	Zhao et al. (2024) [35]
16	Determining the conditions for investing and attracting capital					*		*	*			*	*	*	*	*	*
17	Creating a human resource structure and employment				*			*	*	*	*	*	*	*	*	*	*
18	Build a company					*		*									
19	Advertising and marketing					*											
20	Service control and support					*								*	*	*	
21	Developing networks, attracting credit, and gaining a foothold	*	*			*	*	*	*						*	*	*
22	Counseling and well-being for sustain-ability	*							*	*							

Table 2. *Cont.*

Row	Sub-Process	Van de Ven & Poole (1989) [64]	Vesper (1990) [16]	Gartner and Katz (1988) [14]	Bierley (1985) [65]	Gartner (1985) [61]	Larson and Star (1993) [66]	Veciana (1988) [67]	Deakins & West Ham (2000) [62]	Bohács et al. (2016) [68]	Pearson (2018) [45]	Diamond (2019) [38]	Bitkowsk, (2020) [40]	Amorós et al. (2021) [17]	Doellgast & Wagner (2022) [32]	Vera & Zapata (2022) [41]	Zhao et al. (2024) [35]
23	Strategy-cost leadership					*					*	*	*				
24	Withdrawal of investors according to plan							*					*	*			

Note: * indicates the best-performing result in each row (or column), as reported in the respective studies.

Experts were asked to rate the degree of influence each factor exerts on the others. Responses were analyzed, and any relationship deemed insignificant by at least 50% of the expert panel was eliminated from the model to enhance parsimony and focus. This threshold ensured that the final model retained only meaningful, validated interactions—improving both interpretability and practical utility.

The outcome of this process not only strengthened the internal logic of the process model but also aligned it with AI-supported decision systems, where understanding causal pathways is essential for building intelligent, adaptive workflows. The revised interdependencies among parameters are presented in Table 3, which highlights the directional impact and strength of relationships as identified through the expert-informed DEMATEL framework.

Table 3. Communication matrix and the impact of the factors present in the network relations map.

X	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24
C1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C4	-	-	0.122	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C5	-	-	0.036	0.293	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C6	-	-	0.397	0.452	0.293	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C7	-	0.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C8	-	-	-	-	-	-	0.3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C10	-	0.2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C11	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C12	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C13	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C14	-	0.1	0.326	0.275	0.024	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C15	-	-	0.08	0.067	-	-	-	-	-	-	-	-	-	0.2	-	-	-	-	-	-	-	-	-	-
C16	-	-	0.132	0.145	0.087	0.3	0.1	0.3	-	-	-	-	-	-	0.2	-	-	-	-	-	-	-	-	-
C17	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C18	-	-	-	-	-	-	-	-	-	-	-	-	0.1	-	-	-	-	-	-	-	-	-	-	-
C19	-	-	0.073	0.243	0.017	-	-	0.1	-	-	-	-	-	0.1	0.4	0.171	-	-	-	-	-	-	-	-
C20	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C21	-	-	0.014	0.047	-	-	-	-	-	-	-	-	-	-	0.1	0.033	-	-	0.2	0.122	-	-	-	-
C22	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C23	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
C24	-	-	0.026	0.028	0.017	0.1	-	0.1	-	-	-	-	-	-	-	0.195	-	-	-	-	-	-	-	-

Figure 2 shows the finalized AI-enabled process model for service start-ups that comprehensively integrates decentralized blockchain principles to maximize transparency, traceability, and trust. The model contains 24 validated sub-processes, which reflect a key aspect of the start-up status and an entrepreneur's journey. Each sub-process covers a significant aspect of the start-up process, ranging from idea design/creation, risk evaluation, service presentation/launch, investor withdrawal, etc. The model also shows sequential and parallel flows, both found through the DEMATEL analysis, thus showing that the model is grounded in theory and shows the practical aspects of dynamic start-up cultures.

Figure 3 presents the network relations map derived from DEMATEL analysis, highlighting the causal relationships among the 24 sub-processes. Key drivers such as 'creative idea generation' and 'market research' exhibit strong influence over downstream activities like 'service development' and 'resource collection.' This visualization helps clarify the interdependencies within the model and supports strategic prioritization for start-up founders. The results of the second stage of the survey, along with the statistical tests related to each answer, are summarized in Table 4 to provide a better analysis of the results.

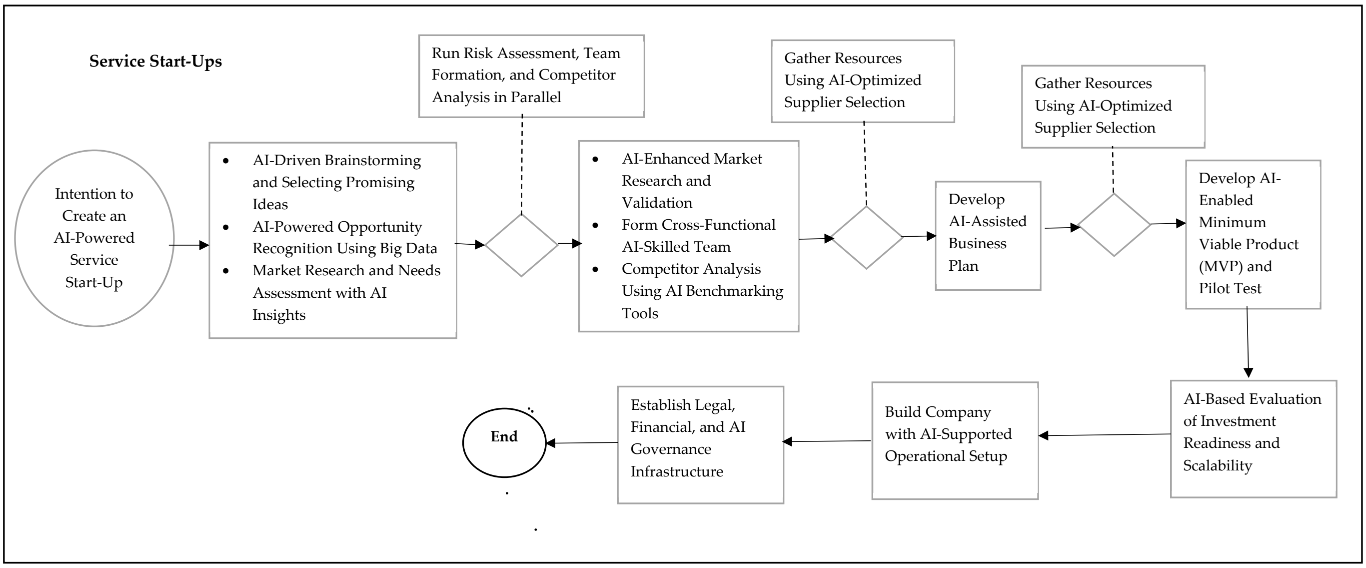

Figure 2. Final process model of technology for service start-ups.

Table 4. Prioritize the components of the service start-up process model.

Priority	Factor	Maximum	Minimum	Standard Deviation	Average
1	Intending to create a startup	5	4	43	4.75
2	Discover and recognize opportunities	5	4	5	4.55
3	Market research, analysis, and needs assessment	5	4	5	4.55
4	Develop and launch a service	5	4	5	4.45
5	Creative idea generation and choosing the best idea	5	3	79	4.35
6	Planning and drawing a business plan	5	4	48	4.35
7	Provide a minimum acceptable product and pilot test	5	3	77	4.25
8	Advertising and marketing	5	4	43	4.25
9	Recognize competitors	5	3	73	4.15
10	Service control and support	5	3	48	4.15
11	Participate with a team with appropriate background and knowledge, and role determination	5	3	73	3.75
12	Achieve the first sale	5	2	83	3.75
13	Create and sell next services and grow	4	3	43	3.75
14	Strategy-cost leadership	5	2	1.13	3.75
15	Risk assessment and rational risk acceptance	4	3	48	3.65
16	Determining the conditions for investing and attracting capital	5	1	1.28	3.65
17	Collecting resources from suppliers	4	3	5	3.45
18	Creating a human resource structure and employment	5	2	97	3.45
19	Developing networks, attracting credit, and gaining a foothold	4	1	1.12	3.45
20	Build a company	5	2	1.6	3.35

Table 4. *Cont.*

Priority	Factor	Maximum	Minimum	Standard Deviation	Average
21	Counseling and well-being for sustainability	4	1	91	3.35
22	Establish a legal, financial and contractual structure	5	1	1.44	3.25
23	Withdrawal of investors according to plan	4	3	43	3.25
24	Collaborate with incubators (accelerators)	3	2	48	2.65

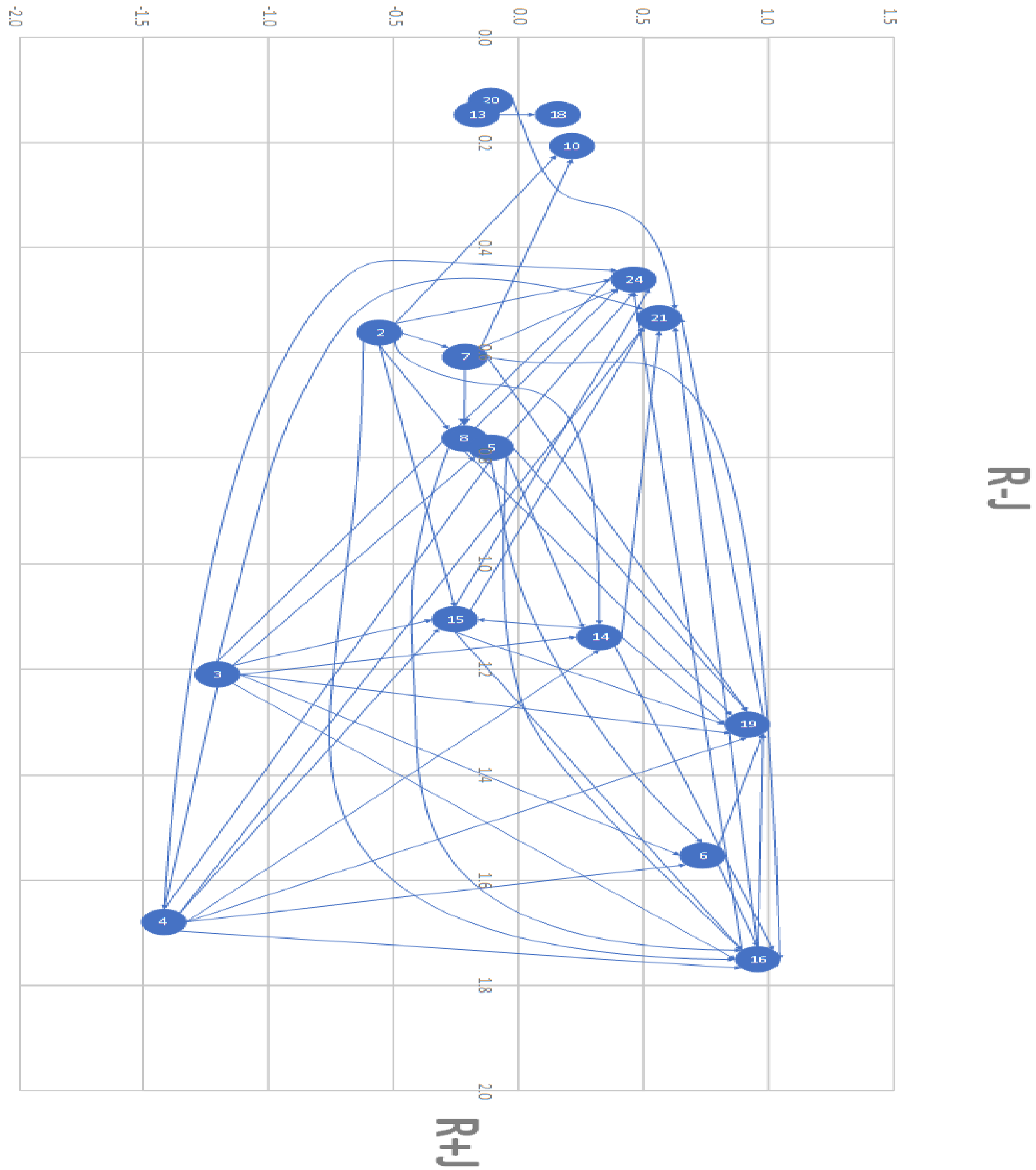

Figure 3. Dematel network relations map based on the final parameter row number.

It was observed that most expert responses clustered around four on the Likert scale. The only exception was the parameter "Collaborate with incubators (accelerators)," which received a lower average rating. However, this outcome was anticipated in the model and, accordingly, the activity was classified as parallel and conditional rather than essential.

One of the core research questions addressed is which parameters are most important in the context of a service start-up. Based on the results discussed above, a list of critical service start-up parameters has been compiled. Another question concerned the relationships among these key parameters. These interrelationships are clearly illustrated in the process model, which defines precedence, latency, sequence, parallelism, and other interaction dynamics. The prioritization in Table 4 highlights foundational activities such as opportunity recognition and service development, which align with early-stage start-up needs. Table 3′s causal mapping reveals which subprocesses act as drivers (e.g., risk assessment) versus those that are reactive (e.g., marketing), informing strategic planning.

Moreover, it is observed that the proposed AI-driven process modeling framework integrates advanced techniques from big data analytics and machine learning to enhance both strategic and operational decision-making. The three main core components (AI-Driven Ideation, AI-Augmented Content, and AI-Enabled Personalization) combine to leverage mind mapping and creative insights to generate innovative ideas for process improvements, provide insights derived from large-scale, unstructured data sources, and apply predictive personalization and real-time insights to tailor processes to customer needs. Developed iteratively based on expert input, the framework functions as a robust, intelligent system for enhancing operational agility, strategic decision-making, and health and safety governance in service-oriented start-ups.

To ensure comprehensive identification and validation of factors influencing the adoption of blockchain- and AI-driven knowledge management systems, we employed a two-round fuzzy Delphi method followed by the DEMATEL technique. The expert questionnaire was structured in two parts: the first contained demographic and professional background questions to confirm the eligibility of participants, and the second part consisted of a series of Likert-scale items designed to evaluate the relevance of each proposed factor.

The initial questionnaire items were derived from an extensive literature review and aligned with constructs from the TAM and TOE frameworks. These were reviewed by two domain experts to ensure content clarity and face validity before distribution. We conducted two Delphi rounds based on best practice guidance that two to three iterations are generally sufficient when consensus stabilizes. The first round gathered initial judgments, while the second round was used to refine consensus after removing items with low reliability or high disagreement.

A total of 18 experts participated in the Delphi process. Experts were selected based on the following criteria:

A minimum of 5 years of professional experience in knowledge management, blockchain, AI, or digital transformation.

- At least a Master's degree in a relevant field (e.g., information systems, data science, or business technology).
- Proven contributions to industry projects or peer-reviewed research related to emerging technologies.
- This ensured that only individuals with significant domain expertise contributed to the questionnaire.

Reliability was assessed using Cronbach's alpha to determine internal consistency of responses. The first-round alpha value was 0.51, indicating a need for revision. Upon further analysis, two items with low item-total correlations were identified and removed. These items showed weak alignment with the rest of the construct and contributed to the overall inconsistency. After removal, the second-round alpha increased to 0.78, indicating acceptable reliability. The improvement supports the view that the Delphi process not only facilitates consensus but also helps refine and strengthen construct reliability through iterative expert feedback.

5. Conclusions

The AI-driven process modeling framework presented in this study integrates advanced techniques from big data analytics and machine learning to support both strategic and operational decision-making in service start-ups. As a result, service start-up processes typically follow a sequence of distinct yet adaptable steps—often referred to as sub-processes or activities, depending on the level of detail and task granularity. Recognizing the variability inherent in these processes, this study aimed to design a flexible, modern process model grounded in Business Process Model and Notation (BPMN), specifically tailored to the unique context of service-based start-ups in Iran, where structured process modeling practices are still emerging. Although the model is validated through expert consensus and causal mapping, empirical testing in live start-up environments is a future research direction. An application pilot or simulation would further substantiate its application.

To ensure a robust and contextually relevant model, the research began with a comprehensive review of prior studies to identify key parameters used in existing start-up process models. These findings were synthesized with practical insights and professional experience to identify 24 sub-processes that collectively define the core operations of service start-ups. Each sub-process was carefully selected and defined to ensure theoretical consistency and alignment with the cultural and operational landscape of the Iranian entrepreneurial ecosystem.

Once the variables were identified, their logical and operational relationships were mapped and visualized through a BPMN model, providing a clear, process-oriented representation of the start-up lifecycle. The model emphasizes agility, service specificity, and a human–technology interaction framework that accommodates digital tools such as AI-powered decision support systems.

To evaluate the relevance and accuracy of these parameters, a two-phase Fuzzy Delphi method was employed alongside a qualitative expert questionnaire. This approach ensured that the model was both theoretically grounded and validated through expert consensus. Experts were asked to rate the importance and clarity of each sub-process on a five-point Likert scale, facilitating nuanced feedback and prioritization.

The structured design enabled iterative refinement of the model, ensuring that it reflects both operational realism and methodological rigor. The final output is a validated, expert-informed process model that can serve as a practical tool for service start-up founders and a foundation for future research in intelligent process automation and strategic planning within entrepreneurial contexts.

To evaluate expert responses, the questionnaire was divided into three sections. The first section collected demographic information, including age, education, work experience, and job title. The second section focused on the importance of the 25 proposed sub-processes. The final section assessed inter-parameter relationships and validated the proposed model.

During the first round of evaluation, one parameter was removed based on expert feedback and concerns about the questionnaire's reliability. In the second round, no changes were recommended by the expert panel. Cronbach's alpha was calculated at 0.74, confirming acceptable reliability. The validity of the questionnaire was further supported through responses to the final validation questions, with a separate Cronbach's alpha score of 0.98, indicating excellent internal consistency.

By confirming both the reliability and validity of the instrument, the research establishes a solid foundation for the model's credibility and applicability. The final BPMN-based model—including its sub-processes and the relationships among them—was formally approved by the expert panel, confirming its readiness for practical implementation.

Finally, the findings underscore the model's potential to facilitate data-informed decision-making in volatile, uncertain, and resource-constrained entrepreneurial environments. It is recommended that active service start-ups, as well as individuals or teams intending to enter this field, review the proposed process model. It can serve as a valuable guide for initiating a start-up or, at the very least, as a planning tool to structure next steps, minimize misunderstandings, and reduce the risk of poor planning.

Limitations and Future Work

This study presents a conceptual framework developed using expert input through fuzzy Delphi and DEMATEL techniques. While this provides a strong theoretical foundation, we acknowledge that the model has not yet been empirically tested in real-world service start-ups. The absence of case studies or pilot applications limits the current practical validation of the proposed model. As a direction for future research, we plan to conduct in-depth case studies and simulations in actual start-up environments to assess the model's functionality, adaptability, and impact on digital transformation initiatives. Such empirical testing will help enhance the model's reliability, offer insights into implementation challenges, and increase its value to practitioners.

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References

1. Zali, M.R.; Razavi, S.M. *Research on Barriers to Entrepreneurship Development in Iran*; Tehran Faculty of Entrepreneurship, University of Tehran: Tehran, Iran, 2008.
2. Gaio, C.; Gonçalves, T.; Venâncio, A. Cash holdings in start-ups: The role of founder sociodemographic characteristics. *J. Bus. Res.* **2022**, *139*, 520–528. [CrossRef]
3. Ruebottom, T.; Toubiana, M. Constraints and opportunities of stigma: Entrepreneurial emancipation in the sex industry. *Acad. Manag. J.* **2021**, *64*, 1049–1077. [CrossRef]
4. Azizi, N.; Akhavan, P.; Philsoophian, M.; Davison, C.; Haass, O.; Saremi, S. Exploring the factors affecting sustainable human resource productivity in railway lines. *Sustainability* **2021**, *14*, 225. [CrossRef]
5. Huang, Z.X.; Savita, K.S.; Jiang, Z.J. The Business Intelligence impact on the financial performance of start-ups. *Inf. Process. Manag.* **2022**, *59*, 102761. [CrossRef]
6. Espinoza-Benavides, J.; Guerrero, M.; Díaz, D. Dissecting the ecosystems' determinants of entrepreneurial re-entry after a business failure. *Eur. Bus. Rev.* **2021**, *33*, 975–998. [CrossRef]
7. Akhavan, P.; Azizi, N.; Akhta ri, S.; Haass, O.; Jan, T.; Sajeev, S. Understanding critical success factors for implementing medical tourism in a multi-case analysis. *Knowl. Manag. E-Learn.* **2023**, *15*, 43.
8. Giaretta, E.; Chesini, G. The determinants of debt financing: The case of fintech start-ups. *J. Innov. Knowl.* **2021**, *6*, 268–279. [CrossRef]
9. Guerrero, M.; Espinoza-Benavides, J. Does entrepreneurship ecosystem influence business re-entries after failure? *Int. Entrep. Manag. J.* **2021**, *17*, 211–227. [CrossRef]
10. Clibborn, S. Australian industrial relations in 2020: COVID-19, crisis and opportunity. *J. Ind. Relat.* **2021**, *63*, 291–302. [CrossRef]
11. Fang, L.; Adelakun, F.; Goetemann, T. Brewing entrepreneurship: Coffee and startups. *J. Plan. Educ. Res.* **2022**, *44*, 1401–1414. [CrossRef]

12. Charekhah, C.; Fartosi, M.; Malayeri, M. *Investing in Startups: Looking at the State of the Country and the Region, Tehran*; Center for the Development of Information Technology and Digital Media: Vancouver, BC, Canada, 2014.
13. Langley, A.N.N.; Smallman, C.; Tsoukas, H.; Van de Ven, A.H. Process studies of change in organization and management: Unveiling temporality, activity, and flow. *Acad. Manag. J.* **2013**, *56*, 1–13. [CrossRef]
14. Gartner, W.B. "Who is an entrepreneur?" is the wrong question. *Am. J. Small Bus.* **1988**, *12*, 11–32. [CrossRef]
15. Katz, J.; Gartner, W.B. Properties of emerging organizations. *Acad. Manag. Rev.* **1988**, *13*, 429–441. [CrossRef]
16. Vesper, K.H. New venture strategies. University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. 1990. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1496217 (accessed on 30 July 2025).
17. Ahmadpour Dariani, M. *Entrepreneurship: Definitions, Theories, Patterns, Company*; Pardis Publication: Tehran, Iran, 2005.
18. Azizi, N.; Malekzadeh, H.; Akhavan, P.; Haass, O.; Saremi, S.; Mirjalili, S. IoT–Blockchain: Harnessing the power of internet of thing and blockchain for smart supply chain. *Sensors* **2021**, *21*, 6048. [CrossRef]
19. Azizi, N.; Haass, O.; Centobelli, P.; Cerchione, R. The impact of cultural practices on the outcome of IT risk management implementation. *Inf. Technol. People* **2024**. [CrossRef]
20. Laine, L.; Kibler, E. The social imaginary of Emancipation in entrepreneurship. *Entrep. Theory Pract.* **2022**, *46*, 393–420. [CrossRef]
21. Yao, M.; Ye, D.; Zhao, L. The relationship between inbound open innovation and the innovative use of information technology by individuals in teams of start-ups. *Syst. Res. Behav. Sci.* **2022**, *39*, 503–515. [CrossRef]
22. Hisrich, R.D.; Peters, M.P.; Sheperd, D.A. *Entrepreneurship, International Edition*; McGraw-Hill: New York, NY, USA, 2005.
23. Azizi, N.; Akhavan, P.; Ahsan, A.; Khatami, R.; Haass, O.; Saremi, S. Influence of motivational factors on knowledge sharing methods and knowledge creation process in an emerging economic context. *Knowl. Manag. E-Learn.* **2023**, *15*, 115.
24. Özkan, E.; Azizi, N.; Haass, O. Leveraging smart contract in project procurement through DLT to gain sustainable competitive advantages. *Sustainability* **2021**, *13*, 13380. [CrossRef]
25. Amorós, J.E.; Leiva, J.C.; Bonomo, A.; Varela, J.C.S. Guest editorial: The entrepreneurship challenges in Latin America. *Eur. Bus. Rev.* **2021**, *33*, 837–848. [CrossRef]
26. Fischer, B.; Meissner, D.; Vonortas, N.; Guerrero, M. Spatial features of entrepreneurial ecosystems. *J. Bus. Res.* **2022**, *147*, 27–36. [CrossRef]
27. Haass, O.; Azizi, N. Knowledge sharing practice in project-oriented organisations: A practical framework based on project life cycle and project management body of knowledge. *Int. J. Proj. Organ. Manag.* **2019**, *11*, 171–197. [CrossRef]
28. Warren, T. Work–life balance and gig work: 'Where are we now' and 'where to next' with the work–life balance agenda? *J. Ind. Relat.* **2021**, *63*, 522–545. [CrossRef]
29. Haass, O.; Azizi, N. Challenges and solutions across project life cycle: A knowledge sharing perspective. *Int. J. Proj. Organ. Manag.* **2020**, *12*, 346–379. [CrossRef]
30. Eliasson, G. From employment to entrepreneurship: Shifting perspectives in Europe and the US on knowledge creation and labour market competition. *J. Ind. Relat.* **2006**, *48*, 633–656. [CrossRef]
31. Schiessl, D.; Korelo, J.C.; Cherobim, A.P.M.S. Corporate social responsibility and the impact on economic value added: The role of environmental innovation. *Eur. Bus. Rev.* **2022**, *34*, 396–410. [CrossRef]
32. Doellgast, V.; Wagner, I. Collective regulation and the future of work in the digital economy: Insights from comparative employment relations. *J. Ind. Relat.* **2022**, *64*, 438–460. [CrossRef]
33. Noh, S.C.; Hebdon, R. Unbundling workplace conflict: Exploring the relationship between grievances and non-strike industrial actions and the moderating effect of voice mechanisms. *J. Ind. Relat.* **2023**, *65*, 22–43. [CrossRef]
34. Schofield-Georgeson, E. The emergence of coercive federal Australian labour law, 1901–2020. *J. Ind. Relat.* **2022**, *64*, 52–76. [CrossRef]
35. Zhao, P.; Zhang, H.; Yu, Q.; Wang, Z.; Geng, Y.; Fu, F.; Yang, L.; Zhang, W.; Jiang, J.; Cui, B. Retrieval-augmented generation for ai-generated content: A survey. *arXiv* **2024**, arXiv:2402.19473.
36. Josserand, E.; Kaine, S. Different directions or the same route? The varied identities of ride-share drivers. *J. Ind. Relat.* **2019**, *61*, 549–573. [CrossRef]
37. Bamber, G.J.; Hoffer Gittell, J.; Kochan, T.A.; Von Nordenflycht, A. Contrasting management and employment-relations strategies in European airlines. *J. Ind. Relat.* **2009**, *51*, 635–652. [CrossRef]
38. Diamond, S. Addressing the imagination gap through STEAMM+ D and indigenous knowledge. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 1851–1856. [CrossRef] [PubMed]
39. Helfen, M.; Sydow, J.; Wirth, C. Service delivery networks and employment relations at German airports: Jeopardizing industrial peace on the ground? *Br. J. Ind. Relat.* **2020**, *58*, 168–198. [CrossRef]
40. Bitkowsk, A. The relationship between Business Process Management and Knowledge Management-selected aspects from a study of companies in Poland. *J. Entrep. Manag. Innov.* **2020**, *16*, 169–193. [CrossRef]

41. Vera, A.; Zapata, C.M. Best practices of business process improvement: Towards a representation on top of the Quintessence kernel. *Bus. Process Manag. J.* **2022**, *28*, 876–903. [CrossRef]
42. Haass, O.; Akhavan, P.; Miao, Y.; Soltani, M.; Jan, T.; Azizi, N. Organizational citizenship behaviour on organizational performance: A knowledge-based organization. *Knowl. Manag. E-Learn.* **2023**, *15*, 85.
43. Ziemba, E.; Eisenbardt, M.; Mullins, R.; Dettmer, S. Consumer engagement in business process innovation–ICT companies' cases from Poland and UK. *J. Comput. Inf. Syst.* **2022**, *62*, 302–315. [CrossRef]
44. Sparx Systems; Maguire, S. Business Modeling Techniques. Available online: https://sparxsystems.com/resources/user-guides/15.1/guidebooks/business-modeling-techniques.pdf (accessed on 30 July 2025).
45. Pearson, S. 9 Best Business Process Modeling Techniques. Tallyfy. 2018. Available online: https://tallyfy.com/business-process-modeling-techniques/ (accessed on 30 July 2025).
46. Pereira, J.L.; Silva, D. Business Process Modeling Languages: A Comparative Framework. In *New Advances in Information Systems and Technologies*; Springer International Publishing: Cham, Switzerland, 2016; pp. 619–628. [CrossRef]
47. Tangkawarow, I.R.H.T.; Waworuntu, J. A Comparative of business process modelling techniques. *IOP Conf. Ser. Mater. Sci. Eng.* **2016**, *128*, 012010. [CrossRef]
48. Nagm-Aldeen, Y.; Abdel-Fattah, M.A.; El-Khedr, A. A Literature Review of Business Process Modeling Techniques. *Int. J.* **2015**, *5*, 43–47.
49. Geyer, R.W.; Fourie, C.J. Determining the suitability of a business process modelling technique for a particular application. *South Afr. J. Ind. Eng.* **2015**, *26*, 252. [CrossRef]
50. Rima, A.; Vasilecas, O.; Šmaižys, A. Comparative analysis of business rules and business process modeling languages. *Comput. Sci. Tech.* **2013**, *1*, 52–60. [CrossRef]
51. Johansson, L.O.; Wärja, M.; Carlsson, S. An evaluation of business process model techniques, using Moody's quality criterion for a good diagram. In *BIR 2012: Emerging Topics in Business Informatics Research 2012, Nizhny Novgorod, Russia*; Rheinisch-Westfaelische Technische Hochschule Aachen, Lehrstuhl Informatik V: Aachen, Germany, 2012; Volume 963, pp. 54–64.
52. Chand, D.R.; Chircu, A.M. Business Process Modeling. In *Business Enterprise, Process, and Technology Management: Models and Applications*; IGI Global: Hershey, PA, USA, 2012; pp. 32–50. [CrossRef]
53. Heidari, F.; Loucopoulos, P.; Brazier, F.; Barjis, J. A Unified View of Business Process Modelling Languages. 2013. Available online: https://www.academia.edu/53673963/A_Unified_View_of_Business_Process_Modelling_Languages (accessed on 30 July 2025).
54. Aldin, L.; De Cesare, S. A Comparative Analysis of Business Process Modelling Techniques. In *UK Academy for Information Systems Conference Proceedings*; UK Academy for Information Systems: Newcastle, UK, 2009.
55. Recker, J. Process modeling in the 21st Century. *BPTrends* **2006**, *3*, 1–6.
56. Aldin, L.; De Cesare, S. A literature review on business process modelling: New frontiers of reusability. *Enterp. Inf. Syst.* **2011**, *5*, 359–383. [CrossRef]
57. Damij, N. Business process modelling using diagrammatic and tabular techniques. *Bus. Process Manag. J.* **2007**, *13*, 70–90. [CrossRef]
58. Ziemann, J.; Matheis, T.; Freiheit, J. Modelling of Cross-Organizational Business Processes—Current Methods and Standards. *Enterp. Model. Inf. Syst. Archit. (EMISAJ)* **2007**, *2*, 23–31. [CrossRef]
59. List, B.; Korherr, B. An evaluation of conceptual business process modelling languages. In Proceedings of the 2006 ACM symposium on Applied computing—SAC '06. SAC06: The 2006 ACM Symposium on Applied Computing, Dijon, France, 23–27 April 2006; Association for Computing Machinery: New York, NY, USA; pp. 1532–1539. [CrossRef]
60. Giaglis, G.M. A Taxonomy of Business Process Modeling and Information Systems Modeling Techniques. *Int. J. Flex. Manuf. Syst.* **2001**, *13*, 209–228. [CrossRef]
61. Gartner, W.B. A Conceptual Framework for Describing the Phenomenon of New Venture Creation. *Acad. Manag. Rev.* **1985**, *10*, 696. [CrossRef]
62. Deakins, D.; Sullivan, R.; Whittam, G. Developing Business Start-up Support Programmes: Evidence from Scotland. *Local Econ. J. Local Econ. Policy Unit* **2000**, *15*, 159–167. [CrossRef]
63. Vashishth, T.K.; Sharma, K.K.; Kumar, B.; Chaudhary, S.; Panwar, R. Enhancing customer experience through AI-enabled content personalization in e-commerce marketing. In *Advances in Digital Marketing in the Era of Artificial Intelligence*; CRC Press: Boca Raton, FL, USA, 2025; pp. 7–32.
64. Van de Ven, A.H.; Poole, M.S. Methods for studying innovation processes. In *Research on the Management of Innovation: The Minnesota Studies*; Oxford University Press: Oxford, UK, 1989; pp. 31–54.
65. Bierley, C.; McSweeney, F.K.; Vannieuwkerk, R. Classical conditioning of preferences for stimuli. *J. Consum. Res.* **1985**, *12*, 316–323. [CrossRef]
66. Larson, A.; Starr, J.A. A Network Model of Organization Formation. *Entrep. Theory Pract.* **1993**, *17*, 5–15. [CrossRef]

67. Veciana Vergés, J.M. Empresari i procés de creació d'empreses. *Rev. Econòmica Catalunya* **1988**, *8*, 53–67.
68. Bohács, G.; Kovács, G.; Rinkács, A. Production Logistics Simulation Supported by Process Description Languages. *Manag. Prod. Eng. Rev.* **2016**, *7*, 13–20. [CrossRef]