DATA-DRIVEN DECISION MAKING IN ENTREPRENEURSHIP: A SYSTEMATIC REVIEW OF BUSINESS GROWTH AND INNOVATION MODELS

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This study investigates the strategic evolution of data-driven entrepreneurship within the contemporary digital landscape. Although data utilization has become widespread, the specific mechanisms facilitating venture growth and innovative resilience remain inconsistently defined in scholarly literature. A systematic literature review was conducted following the PRISMA 2020 protocol, synthesizing twenty-three peer-reviewed articles indexed in the Scopus database. The synthesis revealed that data-driven entrepreneurship functioned as a socio-technical synergy where artificial intelligence acted as a cognitive extension for founders. Findings indicate that analytics-driven strategies increase gross value added by thirty-two percent and enhance user engagement by ten percent. However, ventures faced significant hurdles, including the information technology productivity paradox and algorithmic biases. The research concluded that successful digital scaling required the strategic orchestration of data resources alongside visionary leadership. These results offered a robust framework for navigating the evidentiary logic of modern entrepreneurial ecosystems.

***Kata Kunci*: Artificial intelligence, Big data analytics, Data-driven entrepreneurship, Digital innovation, Systematic literature review.**

I. INTRODUCTION

The rapid advances in digital technology and the emergence of the Fourth Industrial Revolution (Industry 4.0) have fundamentally altered the way individuals and organizations conduct economic activities. Data is now widely regarded as a strategic asset whose value is comparable to conventional resources such as capital and labor. The popular adage comparing data to "the new oil" underscores the immense value contained within information, which must be processed and leveraged to drive progress and profitability [1]. Technological advancements in big data, Artificial Intelligence (AI), and the Internet of Things (IoT) facilitate the collection and analysis of data on a massive scale, enabling business actors to make more accurate, efficient, and evidence-based decisions. For many entrepreneurs, the capacity to manage and analyze this data is a critical prerequisite for navigating business uncertainties.

The proliferation of digital technology and the abundance of data necessitate a fundamental shift in entrepreneurial practices. The conventional approach to entrepreneurship must evolve to effectively respond to the digital transformation's impact on business orientation, behavior, and processes [2]. Specifically, the concept of Data-Driven Entrepreneurship (DDE) focuses on the application of data methods and technologies in executing entrepreneurial activities, including opportunity identification, development, and evaluation. This concept introduces a novel mindset where data is viewed as a core asset, redefining entrepreneurial orientation, culture, and resource management. Data-reliant entrepreneurs leverage informational analysis to reduce uncertainty, expand their knowledge base, and generate insights that lead to effective decision-making.

The data-driven approach offers various strategic opportunities, such as mitigating market uncertainty, expanding business prospects, enhancing firm performance, and optimizing operational efficiency. Nevertheless, DDE implementation is also accompanied by complex challenges, including limited resources, data security concerns, data fatigue, and algorithmic bias [3], [4]. Consequently, many startups fail to fully integrate the principles of Data-Driven Decision Making (DDDM) into their core business strategy. While the topics of entrepreneurship and big data have been extensively discussed, studies specifically focusing on the DDE strategy and its simultaneous contributions to business growth and digital innovation remain fragmented and relatively scarce. A systematic synthesis is still lacking on how entrepreneurs formulate, implement, and overcome challenges related to data-driven strategies to achieve digital competitiveness and innovation.

To address the identified literature gap, this study employs a Systematic Literature Review (SLR) using PRISMA guidelines. The primary focus of this review is to synthesize the most recent literature regarding data-driven entrepreneurship strategies. The study aims to answer the following three primary research questions (RQs):

1) RQ1: How are the core concepts and dimensions of the data-driven entrepreneurship strategy defined in the literature?
2) RQ2: What is the impact and contribution of the data-

driven entrepreneurship strategy on business growth and digital innovation?

3) RQ3: What are the main challenges, constraints, and success factors in implementing the data-driven entrepreneurship strategy?

This review is expected to yield both theoretical and practical contributions. Theoretically, the synthesis will map the conceptual structure and latest developments in DDE research, identify consistent thematic patterns, and highlight prospective research gaps. Practically, the findings will provide evidence-based recommendations for entrepreneurs and policymakers on designing and implementing effective data analytics strategies to maximize business growth and foster innovation.

II. RESEARCH METHODS

A. Systematic Review Approach

This study employs the Systematic Literature Review (SLR) method as the primary methodological approach to identify, critically evaluate, and synthesize literature discussing data-driven entrepreneurship strategies. The choice of SLR is grounded in its ability to generate a transparent, replicable, and low-bias synthesis of knowledge, which aligns with the rigorous standards of interdisciplinary scholarly reviews.

The SLR procedure strictly adheres to the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement [5]. The review process is structured into four main stages: (1) Identification of literature through structured searching, (2) Screening, (3) Eligibility evaluation, and (4) Inclusion of eligible articles for final data synthesis.

B. Search Strategy and Databases

The primary identification of literature was conducted exclusively through Scopus, selected for its comprehensive coverage of high-impact, peer-reviewed journals across management, economics, and computational science. To ensure the findings reflect contemporary technological dynamics and the latest entrepreneurial practices, the publication window was strictly confined to the period between 2020 and 2025.

The search strategy was meticulously developed to achieve a balance between breadth and precision, focusing on the intersection of data-driven mechanisms and entrepreneurial outcomes. Targeted queries were executed within the Title, Abstract, and Keywords (TITLE-ABS-KEY) fields. Table 1 delineates the specific search strings and the strategic rationale for each query.

Table 1. Systematic Search Strings and Query Rationale

Query No.	Focus Area	Search String (TITLE-ABS-KEY)	Keywords Integrated
1	Strategic Orientation & Firm Performance	(("data-driven" OR "data based" OR "data strategy" OR "DDDM") AND (entrepreneurship OR entrepreneurial OR startup OR "new venture") AND (strategy OR "business growth" OR "firm performance"))	Data-driven decision making (DDDM), strategic orientation, and economic scaling.
2	Digital Innovation & Transformation	(("data-driven" OR "data based" OR "data analytics" OR "big data") AND (entrepreneurship OR entrepreneurial OR startup) AND ("digital innovation" OR "digital transformation" OR "digital business model"))	Technological advancement, big data analytics, and digital business model evolution.

C. Article Selection Criteria

The article selection process was executed in structured, sequential phases to guarantee the quality and thematic relevance of the final corpus of literature.

Stage 1: Initial Data Acquisition and Cleaning. The retrieved results were subjected to strict filtering directly within the Scopus database. The applied criteria included: Time Limitation (2020–2025), Document Type (Article), and Language (English). The Subject Area was precisely narrowed to Business, Management, Decision Sciences, Social Science, Computer Science, and Economics. This stage involved crucial data maintenance procedures, including the elimination of duplicates and the removal of retracted publications.

Stage 2: Title and Abstract Screening. The remaining unique articles were individually evaluated based on the relevance presented in their titles and abstracts. The core inclusion criterion mandated that each article must explicitly discuss data-driven entrepreneurship strategies or the implementation of data analytics within an entrepreneurial context correlated with business growth or digital innovation.

Stage 3: Full-Text Eligibility and Inclusion. Potential articles underwent a comprehensive full-text evaluation. To ensure the inclusion of methodologically sound research, each paper was appraised against the following Exclusion Criteria (EC):

- EC1: All forms of secondary research, including existing SLRs, meta-analyses, and bibliometric studies, were excluded to prevent data redundancy and the "double-counting" of primary empirical findings.
- EC2: Articles lacking a clear description of the data-driven mechanism or its specific entrepreneurial application.
- EC3: Articles with insufficient methodological transparency, such as poorly defined data collection procedures or ambiguous analytical frameworks.
- EC4: Non-peer-reviewed content, including editorials, book reviews, and conference abstracts.

The systematic selection process and the resulting attrition of records are meticulously documented in the PRISMA 2020 flow diagram (Figure 1). Initial database identification yielded 314 records, which were subsequently refined through automated filtering and de-duplication to produce a set of 45 records for manual screening. Following the evaluation of titles and abstracts, 19 records were excluded, leaving 26 reports for full-text retrieval. A comprehensive eligibility assessment resulted in the exclusion of 3 further articles based on the EC criteria. Consequently, a final corpus of 23 articles met all inclusion criteria and served as the foundational dataset for synthesis.

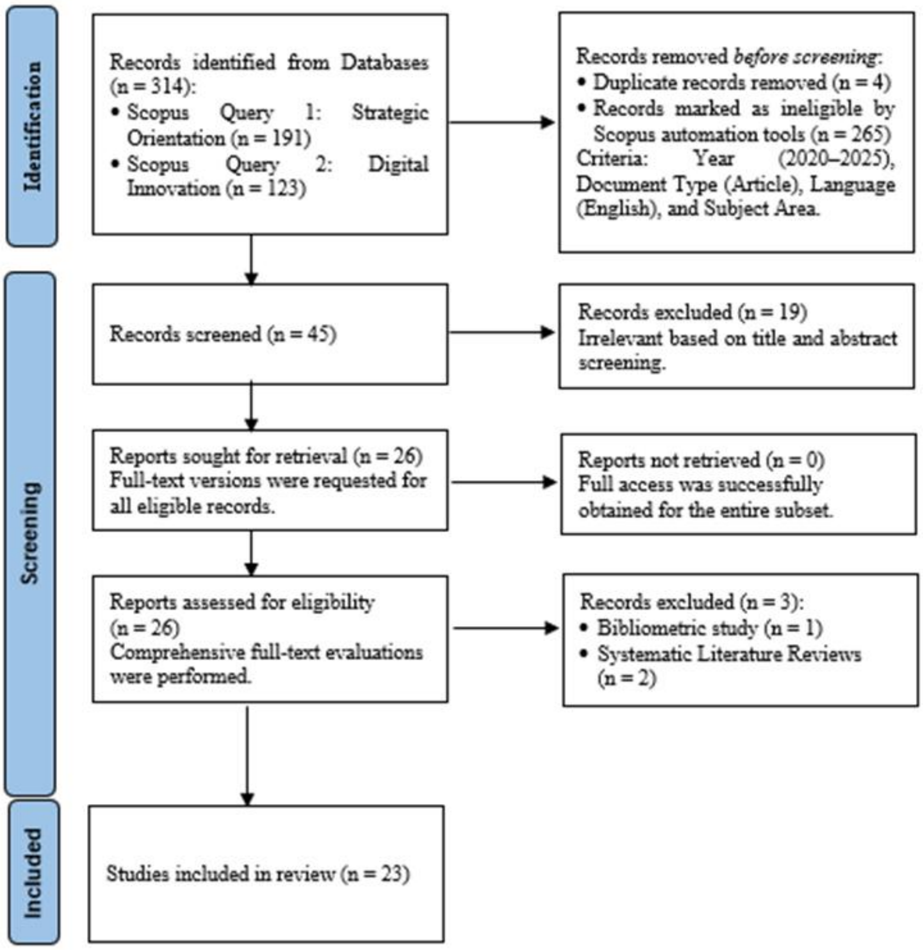

Figure 1. PRISMA 2020 Flow Diagram of the Selection Process

D. Data Extraction and Synthesis Procedures

Relevant data, including metadata and substantive findings for RQ1-RQ3, were systematically extracted from the 23 selected articles. The synthesis followed a hybrid inductive-deductive thematic analysis, combining a pre-defined coding frame with emergent themes from the literature. To ensure inter-rater reliability and mitigate individual bias, the coding process was performed by two independent coders (the authors). Any discrepancies or conflicts in theme categorization were resolved through collaborative consensus-based discussions until 100% agreement was achieved. This rigorous thematic clustering allowed for the identification of key conceptual patterns and the assessment of impacts on growth and innovation, resulting in a coherent and empirically supported narrative.

III. RESULTS AND DISCUSSION

A. Distribution and Methodological Composition of the Corpus

The final selection of 23 articles represents a concentrated cluster of high-impact research that underscores the escalating relevance of data-driven strategies in the current entrepreneurial landscape. Rather than a mere chronological collection, the corpus demonstrates a significant methodological maturation. Quantitative studies comprise the majority of the literature, utilizing sophisticated analytical frameworks such as partial least squares structural equation modeling and hierarchical regressions to validate causal relationships between digital capabilities and venture success [6], [7], [8].

Complementing these statistical insights, qualitative research provides deep contextual understanding through case studies that examine the internal reorganization of firms during technological transitions [9], [10], [11]. Furthermore, the emergence of mixed-methods and computational simulations highlights a trend toward integrating big data mining with traditional business strategy, as seen in recent studies involving LSTM networks and agent-based modeling [12], [13], [14]. This methodological diversity ensures that the synthesis provided in this study is both statistically grounded and contextually rich.

B. Conceptual Evolution and Theoretical Frameworks (RQ1)

The synthesis of the literature regarding the first research question indicates that Data-Driven Entrepreneurship (DDE) has evolved into a comprehensive socio-technical framework. A central theme is the concept of swift resilience, defined by Ye et al. [9] as the ability of a venture to utilize digital innovation for the rapid and mindful reorganization of resources. This is further articulated through the methodology of Growth Hacking, which Schiavone et al.

[10] conceptualize as an iterative process focused on sustainable scalability. Systematic experimentation also emerges as a foundational pillar, where entrepreneurs generate and test strategic options through empirical evidence rather than relying on conventional intuition [15]

A particularly transformative theoretical development is the identification of the human-AI dyad. Jeremiah [16] posits that artificial intelligence serves as a cognitive extension of the entrepreneur, facilitating a transhuman synergy that enhances strategic foresight. This perspective aligns with the theory of dynamic competition, which suggests that firms achieve superior performance by orchestrating data to manage multiple strategic scenarios simultaneously [17]. Grimaldi et al. [2] synthesize these elements by proposing that DDE is supported by four critical dimensions, specifically technological infrastructure, a data-driven mindset, human capital management, and social networks. These conceptualizations collectively suggest that DDE represents a fundamental shift in both entrepreneurial cognition and organizational architecture.

C. Strategic Impacts on Innovation and Economic Performance (RQ2)

In addressing the second research question, the analyzed literature provides robust evidence of the positive correlation between data-driven strategies and measurable growth. Econometric analyses demonstrate that technical collaborations mediated by data analytics can increase the Gross Value Added of small and medium enterprises by 32% [18]. This economic impact is further evidenced in specialized sectors, such as precision agriculture, where AI-driven pathways for student-led projects have yielded a projected initial return on investment of 35% [12].

Innovation analytics has also proven to be a vital instrument for risk mitigation in the digital economy. Mariani and Nambisan [19] illustrate that utilizing online review platforms allows ventures to forecast demand with high precision, thereby preventing substantial financial losses associated with failed designs. The adoption of digital capabilities, particularly digital fluency, enhances a firm's opportunity capability, enabling entrepreneurs to recognize and capture market gaps more effectively [20]. This is supported by the findings of Olórtegui-Alcalde [6], which indicate that digital marketing and process automation significantly strengthen the adaptability of student startups.

Furthermore, the implementation of experimentation tools such as A/B testing is associated with a 10% increase in user engagement and higher rates of feature introduction [15]. In the logistics and retail sectors, analytics-driven procedures have been shown to drastically improve gross profit margins and brand engagement [13], [21]. Even during periods of global crisis, proactive technology adoption has allowed firms to maintain market reach and optimize business solutions [14]. These findings underscore that DDE serves as a critical mediator for achieving sustainable innovation and competitive advantage.

D. Determinants of Success and Implementation Barriers (RQ3)

The third research question explores the duality of success factors and systemic challenges within the DDE framework. The literature identifies the strategic thinking of the CEO as the most influential factor for the success of AI-driven ventures [22]. This leadership must be supported by strong dynamic capabilities, particularly the capacity to sense and seize market opportunities through data orchestration [17]. Additionally, a culture of corporate entrepreneurship and the use of API-driven business models are essential for facilitating value co-creation within broader ecosystems [11], [23].

However, the path to data-driven maturity is often obstructed by the IT productivity paradox, where significant investments in infrastructure fail to produce immediate performance gains due to organizational rigidity [7]. Ethical and technical concerns, such as algorithmic bias and data privacy, pose significant threats to the legitimacy of the entrepreneurial process [16], [24]. Furthermore, information overload can impede the effective utilization of business intelligence, while technological debt remains a persistent risk for ventures that scale too rapidly [8], [10].

External environmental factors also play a decisive role in implementation. Kamysbayev et al. [25] emphasize that coordinated state support and access to financing are primary drivers of eco-innovation in startup ecosystems. In contrast, bureaucratic hurdles and limited venture capital continue to act as significant barriers. In developing regions, infrastructural limitations and regulatory constraints further hinder the adoption of predictive supply chain analytics [26]. Additionally, small firms face unique obstacles related to equity financing and recruitment power [27]. These insights suggest that while DDE offers immense potential, its successful execution requires a careful alignment of internal leadership and external support systems.

E. Synthesis and Data Extraction Matrix

The synthesis of the 23 analyzed articles reveals that Data-Driven Entrepreneurship is a catalyst for higher-order organizational learning. The relationship between digital resources and entrepreneurial outcomes is mediated by the firm's ability to transform raw data into strategic intelligence. The data extraction matrix provided in Table 2 consolidates these findings, mapping each study to its methodological approach and its specific contributions to the research questions.

Table 2. Data Extraction Matrix of Analyzed Studies (N=23)

Author & Year	RQ1: Conceptual Contribution	RQ2: Performance Impact	RQ3: Success & Challenges
Ye et al. (2022)	Swift resilience and modularity.	Exponential revenue growth.	Opportunity sensing.
Dong (2025)	AI-driven smart village precision.	92% yield prediction accuracy.	Technical gradient disappearance.
Jeremiah (2025)	The human-AI dyad concept.	Operational efficiency/personalization.	Ethical and algorithmic bias.
Schiavone et al. (2025)	Growth Hacking methodology.	Process and model innovation.	Technological debt management.
Grimaldi	Technological/	Knowledge	Sectoral and

Author & Year	RQ1: Conceptual Contribution	RQ2: Performance Impact	RQ3: Success & Challenges
et al. (2025)	mindset integration.	creation and innovation.	mindset alignment.
Gupta (2020)	Methodological identification.	32% causal impact on GVA.	Regulatory standards improvement.
Jankovic & Curovic (2023)	AI Adoption Index framework.	Sustainability and efficiency gains.	In-house AI talent availability.
Kim & Jin (2024)	Digital fluency vs literacy.	Opportunity capability mediation.	SME resource constraints.
Kamysbayev et al. (2025)	Startup ecosystem coordination.	12.6% rise in eco-innovation.	Bureaucratic procedures.
Karlsson (2021)	Firm size threshold identification.	Growth barrier categorization.	Equity financing constraints.
Koning et al. (2022)	Experimentation framework.	11% user engagement increase.	High costs of tool adoption.
Lee et al. (2024)	AI startup characteristics.	Market competitiveness drivers.	CEO strategic mind significance.
Mariani & Nambisan (2021)	Innovation Analytics in RORPs.	Forecasting demand/risk reduction.	Protecting knowledge leaks.
Mohammadi et al. (2024)	Patent-based retail ecosystems.	Procedural transformation.	Robust patent strategies.
Petit & Teece (2021)	Dynamic competition/Future rents.	Schumpeterian rents generation.	Rigidity and organizational inertia.
Albahri et al. (2023)	Innovation culture characteristics.	Corporate entrepreneurship weights.	Risk-taking as a success factor.
Olórtegui-Alcalde (2025)	Student startup digital metrics.	Marketing and automation efficiency.	Institutional mentoring support.
Heshmatisafa et al. (2023)	API as a boundary resource.	R&D acceleration and co-creation.	Onboarding self-service risks.
Sakas et al. (2023)	Website engagement metrics.	Gross profit and brand name growth.	High first-year failure rates.
Saura et al. (2023)	Proactive technology adoption.	Reach maintenance during COVID-19.	Cybersecurity and data leaks.
Taifa & Nzowa (2025)	SCM 4.0 implementation.	Predictive analytics performance.	Infrastructural limitations.
Xu & Xu (2025)	BI&A utilization framework.	Absorptive capacity enhancement.	Avoiding information overload.
Zheng & Dai (2025)	Big Data Analytics Capability.	Reduced coordination costs.	The IT productivity paradox.

F. Integrated Conceptual Framework

Based on the synthesis presented in Table 2, Figure 2 illustrates the socio-technical architecture of Data-Driven Entrepreneurship (DDE). This framework suggests that foundational inputs, particularly the convergence of technological infrastructure and the human-AI dyad [16], require transformation through strategic orchestration mechanisms such as Growth Hacking and systematic experimentation [10], [15] to yield measurable strategic outcomes. These results encompass both quantitative economic performance, including a 32% increase in GVA [18], and qualitative digital innovation [9]. Furthermore, this trajectory is moderated by systemic barriers, including the IT Productivity Paradox and algorithmic biases [7], [24], which elucidate the performance variance identified throughout the corpus.

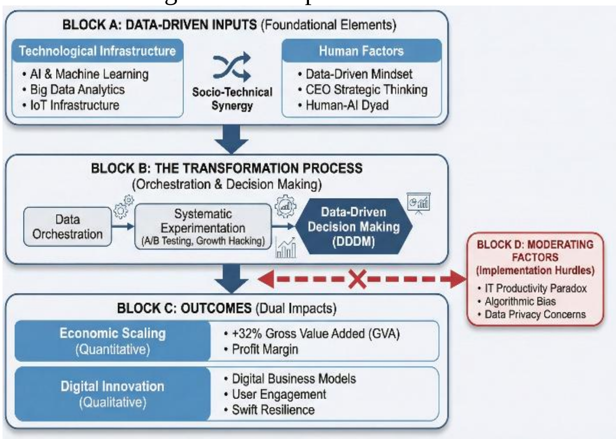

Figure 2. Conceptual Framework of Data-Driven Entrepreneurship as Socio-Technical Synergy

IV. CONCLUSION AND IMPLICATIONS

A. Research Synthesis and Theoretical Contributions

This systematic literature review synthesized twenty-three core articles to define Data-Driven Entrepreneurship (DDE) as a sophisticated socio-technical orchestration of digital resources and human cognition. The findings established that DDE promotes organizational resilience and economic growth, as evidenced by significant increases in firm performance, gross value added, and user engagement [9], [15], [18]. Theoretically, this study integrated the resource-based view with dynamic capabilities, positioning artificial intelligence as a critical cognitive extension that facilitates strategic foresight [7], [16], [17]. By mapping these theoretical intersections, the research provided a unified framework for understanding how ventures transition from intuition-based models to evidence-based strategic logic.

B. Practical and Policy Implications

The practical applications of this research highlight the necessity of cultivating a data-driven culture and a visionary CEO mindset to overcome the information technology productivity paradox [7], [22]. Ventures are encouraged to leverage innovation analytics and API-driven business models to foster ecosystem-wide value co-creation [11], [19]. However, practitioners must remain vigilant against technological debt and the ethical risks associated with algorithmic biases [10], [24]. Furthermore, policy frameworks should prioritize infrastructural development and regulatory clarity to support sustainable digital scaling, particularly in developing and student-led entrepreneurial ecosystems [6], [25], [26].

C. Limitations and Future Research Directions

Future research should pursue longitudinal studies to evaluate the long-term sustainability of data-driven growth models as startups transition into mature corporations. There is also a significant opportunity for comparative studies across different geographical regions to understand how local institutional contexts influence the adoption of DDE strategies. Finally, subsequent scholarly inquiries should prioritize the ethical governance of AI and the psychological impacts of the human-AI dyad on entrepreneurial decision-making, as these areas remain underdeveloped in the current corpus.

DAFTAR PUSTAKA

[1] P. M. Hartmann, M. Zaki, N. Feldmann, and A. Neely, "Capturing value from big data – a taxonomy of data-driven business models used by start-up firms," *Int. J. Oper. Prod. Manag.*, vol. 36, no. 10, pp. 1382–1406, 2016, doi: 10.1108/IJOPM-02-2014-0098.

[2] M. Grimaldi, O. Troisi, A. Papa, and E. de Nuccio, *Conceptualizing data-driven entrepreneurship: from knowledge creation to entrepreneurial opportunities and innovation*, no. 0123456789. Springer US, 2025. doi: 10.1007/s10961-024-10176-5.

[3] Lolade Hamzat, Dare Abiodun, and Abidemi Joseph, "Empowering entrepreneurial growth through data-driven financial literacy, market research, and personalized education tool," *World J. Adv. Res. Rev.*, vol. 19, no. 2, pp. 1692–1711, 2023, doi: 10.30574/wjarr.2023.19.2.1568.

[4] A. N. Turi and X. S. Li, "Data-driven Decision-Making in Digital Entrepreneurship," *Int. J. Ind. Syst. Eng.*, vol. 16, no. 4, pp. 122–127, 2022, [Online]. Available: https://www.researchgate.net/publication/361778286

[5] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *Bmj*, vol. 372, 2021, doi: 10.1136/bmj.n71.

[6] L. M. Olortegui-alcalde and F. Cordova-buiza, "Digital innovation and performance of student startups in Peru : A PLS-SEM evaluation," 2025, doi: 10.21511/ppm.23(4).2025.30.

[7] Y. Zheng and L. Dai, "Corporate Entrepreneurship Driven by Big Data Analytics Capability : A Perspective Based on the Generation and Utilization of Slack Resources," no. March, pp. 1–14, 2025, doi: 10.1177/21582440241305326.

[8] Z. Xu and X. Xu, "Unlocking the secrets of business intelligence and analytics in driving brand innovation : insights from an empirical study using SEM and fsQCA," *Cogent Bus. Manag.*, vol. 12, no. 1, p., 2025, doi: 10.1080/23311975.2025.2494066.

[9] D. Ye, M. J. Liu, J. Luo, and N. Yannopoulou, "How to Achieve Swift Resilience : the Role of Digital Innovation Enabled Mindfulness," *Inf. Syst. Front.*, no. 0123456789, 2022, doi: 10.1007/s10796-021-10225-6.

[10] F. Schiavone, C. Perillo, A. Mandiello, and F. Bernhard, "Growth hacking and network effects : learning for growth and learning," *J. Bus. Res.*, vol. 200, no. July, p. 115594, 2025, doi: 10.1016/j.jbusres.2025.115594.

[11] S. Heshmatisafa, "Exploring API-driven business models : Lessons learned from Amadeus ' s digital transformation," vol. 3, no. May 2022, 2023, doi: 10.1016/j.digbus.2023.100055.

[12] X. Dong, "Smart village construction and college students ' skills entrepreneurship path based on LSTM and simulated annealing algorithm," 2025.

[13] P. Sakas, Damianos, Reklitis, P. Dimitrios, T. Nikolaos, and P. Trivellas, "The influence of websites user engagement on the development of digital competitive advantage and digital brand name in logistics startups," 2023.

[14] J. R. Saura, P.-M. Daniel, and R. Domingo, "Leveraging SMEs technologies adoption in the Covid - 19 pandemic : a case study on Twitter - based user - generated content," *J. Technol. Transf.*, vol. 48, no. 5, pp. 1696–1722, 2023, doi: 10.1007/s10961-023-10023-z.

[15] R. Koning, S. Hasan, and A. Chatterji, "Experimentation and startup performance: Evidence from A/B testing," 2022.

[16] F. Jeremiah, "The human-AI dyad : Navigating the new frontier of entrepreneurial discourse," *Futures*, vol. 166, no. August 2024, p. 103529, 2025, doi: 10.1016/j.futures.2024.103529.

[17] N. Petit and D. J. Teece, "Innovating Big Tech firms and competition policy : favoring dynamic over static competition," no. September, pp. 1168–1198, 2021.

[18] S. Gupta, "Model-Selection Inference for Causal Impact of Clusters and Collaboration on MSMEs in India," no. December, pp. 1–30, 2020.

[19] M. M. Mariani and S. Nambisan, "Innovation analytics and digital innovation experimentation: the rise of research- driven online review platforms," 2021, doi: 10.1016/j.techfore.2021.121009.

[20] J. Kim and W. Jin, "Impact of digital capabilities on entrepreneurial performance in SMEs," *J. Innov. Knowl.*, vol. 9, no. 4, p. 100609, 2024, doi: 10.1016/j.jik.2024.100609.

[21] N. Mohammadi, M. Maghsoudi, and M. Soghi, "Innovation Ecosystems in Retail : Uncovering Technological Trends and Collaboration Networks Through Patent Mining," *IEEE Access*, vol. 12, no. December, pp. 186753–186778, 2024, doi: 10.1109/ACCESS.2024.3515290.

[22] B. Lee and B. Kim, "administrative sciences Enhancing the Competitiveness of AI Technology-Based Startups in the Digital Era," 2024.

[23] O. S. Albahri *et al.*, "Advanced Engineering Informatics Evaluation of organizational culture in companies for fostering a digital innovation using q-rung picture fuzzy based decision-making model," *Adv. Eng. Informatics*, vol. 58, no. September, p. 102191, 2023, doi: 10.1016/j.aei.2023.102191.

[24] S. D. Jankovic and D. M. Curovic, "Strategic Integration of Artificial Intelligence for Sustainable Businesses : Implications for Data Management and Human User Engagement in the Digital Era," 2023.

[25] M. Kamysbayev *et al.*, "Forming an Innovative Start-Up Ecosystem to Increase the Entrepreneurial Activity of Companies (As Exemplified by Asian Countries)," vol. 5, no. 2, pp. 100–115, 2025.

[26] I. W. R. Taifa and J. S. Nzowa, "Implementing Supply Chain Management 4 . 0 : Potential Driving Forces and Strategies From an Empirical Study of Pharmaceutical Industries," 2025, doi: 10.1002/eng2.70190.

[27] J. Karlsson, "Firm size and growth barriers : a data-driven approach," no. May 2020, pp. 1319–1338, 2021.