

Data and Algorithm-Driven Strategies for Building Artificial Intelligence Startups: A Narrative Literature Review

Nabil Hanif Achmaddiredja¹, Herbert Siregar^{2*}

^{1,2} Program Studi Ilmu Komputer, Universitas Pendidikan Indonesia, Bandung, Indonesia

Corresponding author: herbert@upi.edu

ARTICLE INFO

Article history:

26 December 2025

Received in revised form

13 October 2026

Accepted 17 October 2026

Available online 18 October 2026

Keywords:

*artificial intelligence startups,
data strategy, business model
innovation, go-to-market
strategy, scaling readiness*

DOI:

<https://doi.org/10.26740/jieet.v10n01.p51-61>

ABSTRACT

Artificial intelligence and machine learning have become strategic resources that influence how new ventures create value, compete, and scale. However, practical guidance on data and algorithm driven strategies for building such ventures remains dispersed across entrepreneurship, information systems, and sustainability research. This study synthesizes research published from 2020 to 2025 to clarify the strategic choices that shape the development of artificial intelligence and machine learning startups. A narrative literature review was conducted using a structured search in Scopus, with journal articles and review papers screened for relevance and full text accessibility. Twenty five studies were included and analyzed through thematic coding to identify recurring strategy patterns. The results reveal six interrelated strategy domains: business model and value proposition design, go to market and growth in digital and ecosystem settings, capability building for data infrastructure and model operations, analytic approaches for screening and risk assessment, scaling readiness and governance, and responsible practices related to transparency and compliance. The literature indicates that startup advantage depends on aligning data access, algorithmic capabilities, and organizational readiness, as well as sequencing capability development before aggressive scaling. This review provides a consolidated strategy map to support founders and stakeholders in translating research into actionable decisions and highlights gaps for future research on how strategic configurations affect venture outcomes.



This work is licensed under the Creative Commons Attribution
Non-Commercial-Share Alike 4.0 International License.

INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) have moved from supporting tools to strategic resources that can reshape how new ventures discover opportunities, design offerings, and scale. In entrepreneurship, AI is often discussed as an “external enabler” that can augment or replace activities across venture creation (e.g., ideation, selling, and scaling), while also introducing new liabilities and organizational design challenges for early-stage firms. These dynamics make AI relevant not only as a technological choice, but as a strategic one that influences how startups compete and grow (Chalmers et al., 2021)

For AI and ML startups, strategy is frequently intertwined with how data and algorithms shape value creation and defensibility. Prior research on AI startup business models shows that AI startups often differ from typical IT-related business models through (1) value propositions

enabled by AI capabilities, (2) distinct roles of data in value creation, and (3) the influence of AI technology on the overall business logic (Weber et al., 2022). In addition, as sustainability becomes a stronger strategic driver, recent work has mapped “AI startups for good” by proposing a taxonomy and archetypes of sustainable AI-based business models based on empirical instances, indicating that AI can be central to both competitive and societal value creation (Paepflow et al., 2025).

Despite this growing body of work, actionable guidance for “data- and algorithm-driven strategies” in building AI startups remains fragmented across management, information systems, and sustainability outlets. Many studies focus on specific components (e.g., business model patterns or sustainability archetypes) rather than synthesizing strategic choices across an end-to-end startup journey business model design, go-to-market execution, capability development, and scaling. For instance, scaling readiness has recently been operationalized through a holistic framework that integrates governance aspects and AI-driven analytics within innovation ecosystems, suggesting that scaling strategy cannot be treated as a single dimension for startups (Font-Cot et al., 2025). Similarly, AI-first strategy is not automatically beneficial for all firms; it requires explicit choices and readiness to manage both potential and challenges in adopting AI as a strategic cornerstone (Ruokonen & Ritala, 2024).

These strategic tensions are even more pronounced for resource-constrained ventures in sustainability-oriented contexts. In such settings, startups may use AI to innovate business models that aim for measurable environmental impact, which expands the strategic agenda beyond technology development alone (Jorzik et al., 2024; Paepflow et al., 2025).

Motivated by the dispersion of findings and the practical need for a clearer strategy playbook, this literature review synthesizes recent research from 2020 to 2025 on strategies for building AI and ML startups, focusing on how data and algorithms shape strategic decisions across business model design, go-to-market activities, scaling approaches, capability building, and ecosystem positioning. The review adopts a narrative (traditional) literature review approach with transparent search and inclusion logic to provide a structured synthesis without the full procedural overhead of a systematic literature review.

Accordingly, this paper addresses three guiding questions: (1) What data-driven and algorithm-driven strategy themes are most frequently discussed for building AI startups? (2) How do these themes translate into practical strategic choices across business models, go-to-market, and scaling? (3) What recurring challenges and enabling conditions are reported when startups attempt to implement AI-first approaches in real organizational and ecosystem contexts?

METHOD

Research design

This study uses a narrative (traditional) literature review with a structured and transparent process. The approach is suitable when the objective is to synthesize dispersed findings and develop a coherent conceptual understanding rather than to estimate effect sizes or conduct meta-analysis (Snyder, 2019). To increase rigor, the review process was organized using the SALSA

framework (Search, Appraisal, Synthesis, and Analysis), which is commonly used to describe concrete steps in review studies (Grant & Booth, 2009).

Data source and search strategy

The primary database used for literature retrieval was Scopus. Scopus was selected because it provides advanced searching using field tags such as TITLE-ABS-KEY, and allows filtering by year, source type, document type, and publication stage (Scopus advanced search field codes). The search targeted studies on strategies for building AI and ML startups. The final query was executed in Scopus Advanced Search as follows:

The search targeted research on strategies for building AI and ML startups. The query was executed in Scopus Advanced Search using TITLE-ABS-KEY for the core concepts (AI or ML), startup context (startup, new venture, early-stage), and strategy-oriented terms (business model, go-to-market, growth strategy, product strategy, data strategy, AI-first, competitive strategy). The results were then limited to publications from 2020 to 2025, journal sources only, English language, final publication stage, and document types Article or Review.

Inclusion and exclusion criteria

Studies were included when they met all of the following criteria:

1. Discussed AI or ML in the context of startups, new ventures, or early-stage firms.
2. Addressed strategy-related aspects such as business model design, go-to-market, growth strategy, product strategy, data strategy, AI-first strategy, or competitive strategy.
3. Published between 2020 and 2025 in peer reviewed journals and in final publication stage.
4. Full text was accessible for analysis.

Studies were excluded if they met one or more of the following conditions:

1. Used the term startup in a non-entrepreneurial context (for example, startup phase in engineering or healthcare) without implications for startup strategy.
2. Focused primarily on technical algorithm development without clear strategic relevance to venture building.
3. Full text was not accessible for extraction and synthesis.
4. Was not aligned with the scope of AI or ML startup strategy.

Screening and selection procedure

Screening was conducted in two stages. First, title and abstract screening was used to remove records that were clearly out of scope. Second, the remaining records were checked for full-text accessibility and relevance to confirm eligibility for extraction.

The search produced 45 records in the initial Scopus export. After title and abstract screening, 35 records remained for full-text assessment. Of these, 25 studies were included in the final synthesis after confirming relevance and accessibility. To report the selection process

transparently, the study selection is summarized using a PRISMA-style flow diagram (Figure 1). Although this study is not a full systematic review, the PRISMA flow diagram format is widely used to communicate the number of records included and excluded, as well as reasons for exclusion (Page et al., 2021).

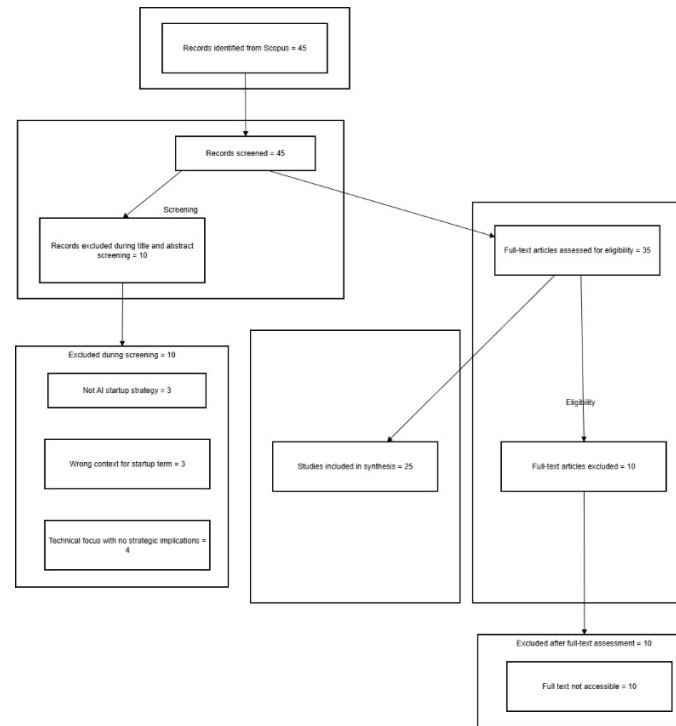


Figure 1. PRISMA Flow Diagram of the Study Selection Process

Data extraction

A structured extraction form was used to ensure consistent capture of evidence from each included study. The extracted information included:

- Bibliographic metadata (authors, year, journal, DOI)
- Study type (conceptual, empirical, case study, or review)
- Context (industry domain, geography if available, and startup stage if stated)
- Strategy focus (business model, go-to-market, growth, product, data strategy, AI-first positioning, scaling, ecosystem positioning, and governance)
- Key findings and practical implications for startup strategy

Synthesis and analysis

The included studies were synthesized using thematic analysis to identify recurring strategy themes and to organize findings into a coherent framework (Braun et al., 2008).

Coding was conducted iteratively to develop and refine themes across studies. The synthesis also followed thematic synthesis principles to preserve transparent links between extracted evidence and the resulting themes (Thomas & Harden, 2008).

Rigor and trustworthiness

Three steps were used to improve rigor and reduce bias:

- Transparent reporting of the database, search scope, and filtering logic (Snyder, 2019).
- Use of explicit inclusion and exclusion criteria during screening and full-text assessment (Grant & Booth, 2009).
- Consistent extraction fields and iterative theme development to ensure themes reflect patterns across multiple studies (Braun et al., 2008).

Table 1. The Example of the Table Format

Aspects	Functions
Aspect_One	Function_One
Aspect_Two	Function_Two
Aspect_Three	Function_Three
Aspect_Four	Function_Four
Aspect_Five	Function_Five

RESULTS

Study Selection

The initial search and filtering process resulted in 45 records after applying Scopus filters for publication year (2020–2025), journal-source, English language, and final publication stage. Titles and abstracts were screened to exclude clearly out-of-scope records, and full-text availability was verified. After this screening process, 25 articles were retained for inclusion in the final synthesis. The remaining 10 records were excluded due to unavailability of full text or insufficient relevance to the strategic context of building AI/ML startups (Aprillia et al., 2024; Battisti et al., 2022; Brecht et al., 2021; Font-Cot et al., 2025; Gerlich et al., 2025; Ghanimi et al., 2024; Gupta, 2024; Holzinger et al., 2025; Jafri et al., 2025; Jorzik et al., 2024; Kapsis, 2020; Li et al., 2024; Lu & Yu, 2022; Maarouf et al., 2025; Ostermann et al., 2021; Paepflow et al., 2025; Perifanis & Kitsios, 2023; Piskunova et al., 2021; Potsulin et al., 2024; Ruokonen & Ritala, 2024; Sánchez García et al., 2025; Saura et al., 2021; Voloshyna-Sidei et al., 2025; Weber et al., 2022; Zhou et al., 2021).

The selection process is illustrated in Figure 1, which follows a PRISMA-style format to transparently describe the review pipeline.

Overview of Included Studies

Table 1. Distribution of Included Studies by Publication Year (n = 25)

Year	Number of Studies
2020	1
2021	5
2022	3
2023	1
2024	7
2025	8

The distribution indicates a growing academic interest in strategic aspects of AI and ML startups, with higher numbers of publications in 2024 and 2025.

Table 2. Research Methods Used in the Included Studies (n = 25)

Methodological Approach	Number of Studies
Empirical/other	8
Case study	5
Machine learning modeling	4
Theoretical/framework	3
Survey/structural modeling	3
Bibliometric analysis	1
Literature review article	1

This composition shows that empirical studies, including case studies, represent the majority, while a smaller portion uses predictive modeling or conceptual frameworks relevant to strategy.

Thematic Synthesis of Strategy Insights

Thematic analysis across the included articles identified six major strategy themes that are recurrent in the literature on building AI and ML startups.

Table 3. Major Strategic Themes Identified (n = 25)

Strategic Theme	Count
Business model and value proposition	7
Go-to-market, growth, and ecosystems	6
Screening, prediction, and risk assessment	4
AI-first strategy and capability building	4
Regulation and responsible AI	2
Scaling, governance, and contextual strategy	2

- **Business Model and Value Proposition**

Several studies emphasize that the role of AI goes beyond technical deployment and affects the core value proposition and business logic of startups. These studies suggest that AI and data can be central assets in defining how value is created, delivered, and captured in AI startups, including options for monetization and revenue structure.

- **AI-first Strategy and Capability Building**

The literature highlights that adopting an AI-first strategic orientation requires organizational readiness and explicit decisions about integration of AI capabilities. This includes establishing data infrastructure, model governance, and choices between building internal capabilities or relying on external partners.

- **Go-to-Market, Growth, and Ecosystems**

Articles within this theme focus on strategies for market penetration, experimentation with product–market fit, and leveraging digital channels to accelerate growth. The literature also points to the role of ecosystem actors in supporting market adoption and co-creation.

- **Screening, Prediction, and Risk Assessment**

This theme includes studies that apply data analytics or machine learning techniques to support decision-making in early venture stages, such as predicting startup success, evaluating opportunities, and prioritizing strategic investment decisions. These analytical methods highlight how data and narrative features can act as strategic signals.

- **Scaling, Governance, and Contextual Strategy**
A smaller cluster of studies deals with the challenges of scaling AI startups. These works suggest that readiness for scaling involves multiple dimensions including team capabilities, resources, governance models, and interaction with broader innovation ecosystems.
- **Regulation and Responsible AI**
Studies categorized under this theme discuss how regulations and ethical considerations influence strategic decision-making in AI startups. Topics include transparency requirements, regulatory compliance, and human oversight, which are relevant for gaining market trust and ensuring long-term sustainability.

Consolidated Strategy Dimensions

Table 4. Strategy Dimensions and Their Strategic Implications

Strategy Dimension	Key Insights	Example Strategic Decisions Influenced by Data and AI
Business model design	AI reshapes value propositions and revenue structures	Choosing between AI-centric product, service, or analytics business models
Go-to-market & growth	Market engagement is driven by experimentation and digital channels	Defining customer acquisition experiments and prioritizing go-to-market channels
Capability building	AI-first strategies require structured capability development	Building data pipelines, model operations, and governance practices
Scaling strategy	Scaling readiness involves internal and external factors	Assessing team skills, product maturity, and ecosystem readiness before expansion
Screening & risk assessment	Predictive tools support prioritization and opportunity evaluation	Using analytical models for opportunity ranking and risk forecasting
Responsible AI & regulation	Ethical frameworks and compliance affect adoption and trust	Establishing AI transparency policies and human oversight mechanisms

Table 4 summarizes the key strategic dimensions extracted from the literature and aligns them with practical decisions that founders, investors, or strategists may face when building AI-driven ventures.

DISCUSSION

This review set out to consolidate strategy-oriented insights on building AI and ML startups, with emphasis on how data and algorithms shape decisions across business models, go to market, capability building, scaling, and governance. The synthesis shows that “AI strategy” in

startups is rarely a single decision. It is a bundle of interdependent choices that affect venture creation activities, organizational design, and execution risks (Chalmers et al., 2021).

RQ1. Dominant data and algorithm driven strategy themes

Across the included studies, the most consistent themes were business model design, go to market and growth choices, capability building, prediction and risk assessment, scaling readiness, and responsible AI considerations. This pattern aligns with prior entrepreneurship work that frames AI as both an enabler of venture activities and a source of new liabilities, such as dependence on data quality, model performance, and organizational readiness (Chalmers et al., 2021).

RQ2. Translating themes into practical strategic choices

- **Business model and value proposition**
A recurring point is that AI startups should not treat AI as a feature add on. The business model needs to specify how AI capabilities and data roles create value and defensibility. Weber et al. show that AI startup business models differ from common IT related business models through AI enabled value propositions, distinct roles of data in value creation, and the impact of AI on overall business logic (Weber et al., 2022). Practically, this means founders must be explicit about what the algorithm does for customers, what data is required, and how learning effects or data access create advantage.
- **Go to market, growth, and ecosystems**
The evidence indicates that go to market decisions are intertwined with data strategy. AI products often require feedback loops, user adoption that produces useful data, and careful design of onboarding and evaluation to prove value. In many AI startup contexts, ecosystem positioning matters because access to data, distribution, and domain validation often depends on partners rather than internal assets alone (Chalmers et al., 2021). This suggests founders should treat partner selection and integration strategy as part of go to market design, not as a later operational concern.
- **AI first strategy and capability building**
Ruokonen and Ritala emphasize that an AI first strategy is not automatically beneficial and requires deliberate choices and readiness to manage both potential and challenges (Ruokonen & Ritala, 2024). In practice, this maps to capability decisions such as data infrastructure, model operations, governance, and talent. The key strategic implication is sequencing. Startups can fail by scaling marketing before building reliable model operations, or by building sophisticated models before confirming a stable data acquisition mechanism.
- **Screening, prediction, and risk assessment**
A smaller but important cluster highlights how predictive analytics can support prioritization decisions. These approaches are useful for founders and investors when uncertainty is high, but they also raise issues of bias, interpretability, and data representativeness. This aligns with the broader AI strategy view that algorithms are decision tools that need governance and contextual judgment, especially when used for resource allocation and selection.

- **Scaling, governance, and readiness**
Scaling is repeatedly described as multidimensional rather than linear. The Scaling Wheel Framework argues that scalability readiness can be strengthened by examining multiple modules, including team, competitive environment, product and service, capital and resources, and strategy and timing, with attention to governance and analytics in innovation ecosystems (Font-Cot et al., 2025). For AI startups, this reinforces a practical approach: do not treat scaling as only growth metrics. Treat it as a readiness assessment across product reliability, data pipelines, and governance.
- **Responsible AI and regulation**
Although fewer studies directly focus on regulation, the theme is strategically meaningful. Trust, transparency, and compliance can become market enablers in regulated or high risk domains. This is consistent with the argument that AI changes organizational design and introduces liabilities that require management, not only technical improvement (Chalmers et al., 2021).
- **Sustainability oriented contexts as a strategic modifier**
Even when sustainability is not the primary focus, several strategy choices change in sustainability oriented settings. Research on sustainable AI startup business models proposes taxonomies and archetypes that show how AI can be configured to create both societal and competitive value (Paepelow et al., 2025). Related work on green technology startups argues that AI can drive business model innovation aimed at environmental sustainability (Jorzik et al., 2024). The implication for your review topic is that “data and algorithm driven strategy” is not only about optimization. It can also be about designing measurable impact, which affects metrics, partners, and governance expectations.

RQ3. Recurring challenges and enabling conditions

Across themes, the challenges cluster into a few repeatable categories:

1. Data acquisition and quality constraints, which affect product reliability and defensibility (Weber et al., 2022).
2. Capability and readiness gaps, especially when adopting an AI first posture without the required organizational foundations (Ruokonen & Ritala, 2024).
3. Scaling and governance complexity, where growth exposes weaknesses in processes, ecosystem dependencies, and accountability structures (Font-Cot et al., 2025).
4. Liabilities introduced by AI, including new ways of working and risks from technological leverage (Chalmers et al., 2021).

Enabling conditions also recur: explicit strategy choices about AI scope, disciplined sequencing of capability building before aggressive scaling, and careful ecosystem positioning for data and distribution access.

CONCLUSION

This narrative literature review synthesizes research from 2020 to 2025 on strategies for building AI and ML startups, focusing on how data and algorithms influence strategic decision making. The synthesis identifies six recurring strategy domains: business model design, go to market and growth, capability building for AI first approaches, prediction and risk assessment, scaling readiness and governance, and responsible AI considerations. The evidence suggests that

competitive advantage in AI startups comes less from using AI in general and more from configuring the business model and organizational capabilities around data roles, learning processes, and governance (Chalmers et al., 2021; Weber et al., 2022).

Practical implications

For founders, the findings imply that a strategy playbook should include explicit choices about (1) the AI value proposition and data dependence, (2) how go to market activities create feedback loops, (3) the capability stack required for reliable model operations, and (4) scaling readiness across governance and ecosystem dependencies. For investors and ecosystem stakeholders, the results support a multidimensional view of scalability and readiness rather than focusing only on growth indicators (Font-Cot et al., 2025).

Limitations

This review is limited by its narrative design and by choices that constrain coverage. The study relies on Scopus, English language publications, a defined time window, and accessible full texts, which may introduce selection bias and omit relevant work available in other databases or languages. These limitations are consistent with common trade offs in traditional literature reviews, which can be strengthened through transparent reporting and structured synthesis (Snyder, 2019).

Future research directions

Future studies can strengthen the field by (1) testing causal links between AI first strategy choices and startup outcomes, (2) developing clearer guidance on sequencing capability building and go to market execution, (3) examining governance and responsible AI practices specifically in early stage contexts, and (4) expanding evidence across regions and sectors to reduce context bias (Font-Cot et al., 2025; Ruokonen & Ritala, 2024).

REFERENCES

- Aprillia, A., Kuswoyo, C., Kristiawan, A., Sunarjo, R. A., & Awhina, R. A. Te. (2024). Cyberpreneurship Research Trends and Insights from 1999 to 2023. *APTISI Transactions on Technopreneurship*, 6(3), 390–403. <https://doi.org/10.34306/att.v6i3.421>
- Battisti, S., Agarwal, N., & Brem, A. M. (2022). Creating new tech entrepreneurs with digital platforms: Meta-organizations for shared value in data-driven retail ecosystems. *Technological Forecasting and Social Change*, 175. <https://doi.org/10.1016/j.techfore.2021.121392>
- Braun, V., Clarke, V., Braun, V., & Clarke, V. (2008). *Using thematic analysis in psychology*. 0887(2006).
- Brecht, P., Niever, M., Kerres, R., Ströbele, A., & Hahn, C. H. (2021). Smart platform experiment cycle (SPEC): A process to design, analyze, and validate digital platforms. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM*, 35(2), 209–225. <https://doi.org/10.1017/S0890060421000081>
- Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial Intelligence and Entrepreneurship: Implications for Venture Creation in the Fourth Industrial Revolution. *Entrepreneurship: Theory and Practice*, 45(5), 1028–1053.

- <https://doi.org/10.1177/1042258720934581>
- Font-Cot, F., Lara-Navarra, P., Arnau, C. S., & Serradell-Lopez, E. (2025). Scaling Wheel Framework: A holistic approach to startup scalability, governance models, and AI-driven innovation ecosystem competitiveness. *Journal of Open Innovation: Technology, Market, and Complexity*, 11(3). <https://doi.org/10.1016/j.joitmc.2025.100619>
- Gerlich, C., Brenk, K., Antonio, J. L., Kanbach, D. K., & Kraus, S. (2025). Wielding a double-edged sword: Unravelling the development of dynamic capabilities through growth hacking. *Journal of Business Research*, 189. <https://doi.org/10.1016/j.jbusres.2024.115172>
- Ghanimi, H. M. A., Painoli, G. K., Contractor, D., Sowjanya, G. N., Vani Lavanya, A., & Poon, K. (2024). Analyzing the Impact of Scientific and Technological Innovations on Financial Performance: A PCA-Based Study of an AI Healthcare Startup. *Journal of Machine and Computing*, 4(4), 1117–1125. <https://doi.org/10.53759/7669/jmc202404103>
- Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information and Libraries Journal*, 26(2), 91–108. <https://doi.org/10.1111/j.1471-1842.2009.00848.x>
- Gupta, V. (2024). An Empirical Evaluation of a Generative Artificial Intelligence Technology Adoption Model from Entrepreneurs' Perspectives. *Systems*, 12(3). <https://doi.org/10.3390/systems12030103>
- Holzinger, J., Nagl, A., Bozem, K., Lecon, C., Ensinger, A., Rößler, J., & Neufeld, C. (2025). Business Case for a Regional AI-Based Marketplace for Renewable Energies †. *Sustainability (Switzerland)*, 17(4). <https://doi.org/10.3390/su17041739>
- Jafri, S., Upreti, K., Bhardwaj, R., Verma, B., & Jain, R. (2025). Harnessing mobile multimedia for entrepreneurial innovation and sustainable business growth. *International Journal of Systematic Innovation*, 9(4), 54–70. [https://doi.org/10.6977/IJoSI.202508_9\(4\).0005](https://doi.org/10.6977/IJoSI.202508_9(4).0005)
- Jorzik, P., Antonio, J. L., Kanbach, D. K., Kallmuenzer, A., & Kraus, S. (2024). Sowing the seeds for sustainability: A business model innovation perspective on artificial intelligence in green technology startups. *Technological Forecasting and Social Change*, 208. <https://doi.org/10.1016/j.techfore.2024.123653>
- Kapsis, I. (2020). A Truly Future-Oriented Legal Framework for Fintech in the EU. *European Business Law Review*, 31(3), 475–514. <https://doi.org/10.54648/eulr2020020>
- Li, J., Meng, M., Liu, X., Lv, Y., & Yu, J. (2024). Evaluation and screening of technology startups based on PCA and GA-BPNN. *PLOS ONE*, 19(2 February). <https://doi.org/10.1371/journal.pone.0289691>
- Lu, S., & Yu, H. (2022). Research on Digital Business Model Innovation Based on Emotion Regulation Lens. *Frontiers in Psychology*, 13. <https://doi.org/10.3389/fpsyg.2022.842076>
- Maarouf, A., Feuerriegel, S., & Pröllochs, N. (2025). A fused large language model for predicting startup success. *European Journal of Operational Research*, 322(1), 198–214. <https://doi.org/10.1016/j.ejor.2024.09.011>
- Ostermann, C. M., Nascimento, L. D. S., & Zen, A. C. (2021). Business Model Innovation for Circular Economy in Fashion Industry: A Startups' Perspective. *Frontiers in Sustainability*, 2. <https://doi.org/10.3389/frsus.2021.766614>
- Paepflow, J., Schoormann, T., Moller, F. O., & Strobel, G. (2025). AI startups for good: A taxonomy and archetypes of sustainable business models. *Journal of Cleaner Production*, 520. <https://doi.org/10.1016/j.jclepro.2025.146144>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S.,

- ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *Bmj*, 372. <https://doi.org/10.1136/bmj.n71>
- Perifanis, N.-A., & Kitsios, F. (2023). Investigating the Influence of Artificial Intelligence on Business Value in the Digital Era of Strategy: A Literature Review. *Information (Switzerland)*, 14(2). <https://doi.org/10.3390/info14020085>
- Piskunova, O. V., Ligonenko, L. O., Klochko, R., Frolova, T., & Bilyk, T. (2021). Applying Machine Learning Approach to Start-up Success Prediction. *Scientific Horizons*, 24(11), 72–84. [https://doi.org/10.48077/scihor.24\(11\).2021.72-84](https://doi.org/10.48077/scihor.24(11).2021.72-84)
- Potsulin, A., Sergeeva, I. G., Alexandrova, A., Kuporov, Y. Y., & Shik, I. (2024). Developing a Model for Forecasting Risks of Innovative Entrepreneurial Projects with Machine Learning Tools. *Pakistan Journal of Life and Social Sciences*, 22(2), 2549–2561. <https://doi.org/10.57239/PJLSS-2024-22.2.00186>
- Ruokonen, M., & Ritala, P. (2024). How to succeed with an AI-first strategy? *Journal of Business Strategy*, 45(6), 396–404. <https://doi.org/10.1108/JBS-08-2023-0178>
- Sánchez García, P., Díez-Gracia, A., Mayorga, I. R., & Jerónimo, P. (2025). Media Self-Regulation in the Use of AI: Limitation of Multimodal Generative Content and Ethical Commitments to Transparency and Verification. *Journalism and Media*, 6(1). <https://doi.org/10.3390/journalmedia6010029>
- Saura, J. R., Reyes-Menendez, A., De Matos, N. M. S., & Correia, M. B. (2021). Identifying startups business opportunities from ugc on twitter chatting: An exploratory analysis. *Journal of Theoretical and Applied Electronic Commerce Research*, 16(6), 1929–1944. <https://doi.org/10.3390/jtaer16060108>
- Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104(March), 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
- Thomas, J., & Harden, A. (2008). *Methods for the thematic synthesis of qualitative research in systematic reviews*. 10, 1–10. <https://doi.org/10.1186/1471-2288-8-45>
- Voloshyna-Sidei, V., Onishchenko, S., Zhydovska, N., Borodenko, T., & Abramova, M. (2025). The Influence of Fintech Startups on the Dynamics of Innovative Development of the Financial Market. *Management (Montevideo)*, 3. <https://doi.org/10.62486/agma2025218>
- Weber, M., Beutter, M., Weking, J., Böhm, M., & Krcmar, H. A. O. (2022). AI Startup Business Models: Key Characteristics and Directions for Entrepreneurship Research. *Business and Information Systems Engineering*, 64(1), 91–109. <https://doi.org/10.1007/s12599-021-00732-w>
- Zhou, J., Yang, J., Sun, H., Liu, Y., & Liu, X. (2021). The Influence of Entrepreneurial Cognition on Business Model Innovation: A Hybrid Method Based on Multiple Regressions and Machine Learning. *Frontiers in Psychology*, 12. <https://doi.org/10.3389/fpsyg.2021.744237>