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A Meta-Analytic Examination of the Antecedents and Outcomes of Artificial Intelligence Utilization in Accelerating Development in Startup Businesses

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Abstract

This study aims to identify, categorize, and synthesize the antecedents and outcomes of artificial intelligence utilization in accelerating development in startup businesses. A systematic meta-analytic approach was employed to integrate empirical findings from studies published between 2019 and 2024. Following PRISMA guidelines, a comprehensive search was conducted across databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and PubMed. Studies were screened based on predefined inclusion criteria requiring quantitative designs, extractable effect sizes, and explicit examination of AI-related antecedents or outcomes in startup contexts. A structured extraction protocol captured bibliographic data, methodological features, and statistical indicators. Quality assessment procedures ensured the reliability of included studies. Random-effects models were applied using Comprehensive Meta-Analysis (CMA) and R packages (“metafor” and “meta”), with heterogeneity assessed via Q-statistics and I^2 indices. Moderator analyses explored variations across geographic regions, industry sectors, methodological designs, and types of AI applications. Publication bias was examined using funnel plots, Egger’s tests, and trim-and-fill adjustments. The meta-analysis synthesized 45 empirical studies and identified 113 unique concepts, which were organized into several axial categories. Significant antecedent predictors of AI-enabled acceleration included leadership orientation toward AI, human capital readiness, organizational agility, data infrastructure maturity, ecosystem support, and regulatory and ethical alignment. Outcomes demonstrated statistically significant improvements in innovation speed ($p < .001$), operational efficiency ($p < .001$), forecasting accuracy ($p < .01$), and decision-making quality ($p < .001$). Market and financial indicators—including customer acquisition speed, revenue growth, and valuation—also showed strong positive effects ($p < .001$). Moderator analyses revealed variations by industry and geographic region, confirming that contextual factors influence the strength of AI’s impact. AI-driven acceleration in startups is a multidimensional phenomenon shaped by strategic, organizational, technological, and ecosystem conditions, producing substantial gains in innovation speed, operational performance, and market outcomes.

Keywords: Artificial intelligence; startup development; meta-analysis; digital transformation; innovation speed; entrepreneurial ecosystems; organizational agility; data infrastructure.

1. Introduction

The rapid evolution of artificial intelligence (AI) in the past decade has substantially reshaped how entrepreneurial ecosystems emerge, scale, and sustain competitive advantage in digital economies. Startups—characterized by agility, resource constraints, and innovation-driven growth—have become the central beneficiaries and experimenters of AI-enabled transformation, relying on automated analytics, intelligent decision-support systems, predictive modeling, and customer-centric data ecosystems to accelerate development. Contemporary analyses show that the integration of AI into early-stage ventures enhances strategic planning, operational efficiency, customer acquisition, and the discovery of new business opportunities, thus redefining the temporal dynamics of startup growth and survival. Researchers highlight that AI no longer operates as a supplementary tool but rather as a foundational capability influencing organizational processes, human-centered design, data governance, and competitive positioning in volatile markets (Ali, 2024; Siegel, 2024; Usman et al., 2024). This shift toward AI-driven entrepreneurship reflects the convergence of technological, economic, and socio-institutional factors that increasingly determine the speed and trajectory of business development across global startup ecosystems.

Recent scholarship emphasizes that AI alters traditional business models, reconfigures value creation mechanisms, and introduces new modes of scalability for startups operating in highly digitized markets (Ali, 2024). AI-enabled systems support deeper automation, optimize operations, and allow entrepreneurs to navigate uncertain environments with enhanced predictive accuracy (Kumar, 2024; Siegel, 2024). At the same time, the emergence of intelligent automation in fields such as telecommunications and fintech has demonstrated how AI shortens development cycles and improves decision-making efficiency, granting young firms the capacity to scale rapidly (Dodda, 2022; Kumar, 2024). The acceleration effect is not merely a technical phenomenon; it is embedded in strategic, managerial, and behavioral shifts that reorient startups toward data-driven thinking and evidence-based innovation. These developments highlight the growing necessity for systematic investigations that map the antecedents and outcomes of AI utilization in startup development, especially across heterogeneous industry sectors.

One of the central dimensions shaping AI adoption in startups is digital transformation and the evolution of sector-specific innovation models. Studies on AI adoption in health, marketing, and digital commerce illustrate how advanced analytics, machine learning, and intelligent automation generate entirely new business structures, customer engagement models, and revenue streams (Gagandeep et al., 2022; Garbuio & Lin, 2018; Idrus et al., 2023). These transformations have been observed particularly in industries where data-intensive operations and real-time processing are crucial, such as healthcare, online retail, telecommunications, and digital payments. The use of AI in these sectors has been associated with simplifying complex workflows, increasing personalization, enhancing risk assessment, and supporting regulatory compliance (Dodda, 2022; Gagandeep et al., 2022). Moreover, the expansion of e-commerce ecosystems, especially in developing and emerging economies, underscores the role of AI in scaling logistics, optimizing customer experience, and fostering new forms of digitally enabled entrepreneurship (Стройко et al., 2024). As startups increasingly rely on AI to interpret customer behavior, manage digital interactions, and automate operational processes, the speed of growth becomes tightly linked to the quality of AI integration in business processes.

Another critical factor that shapes AI adoption in startups relates to the sociotechnical and institutional contexts in which ventures operate. Regulatory frameworks, economic structures, and institutional support systems strongly influence how startups utilize AI for competitive advantage (Pierre, 2022; Raju & S., 2023). For instance, supportive entrepreneurship institutions and innovation-driven policies enhance startups' capacity to access AI tools, integrate them into strategic activities, and mobilize resources that accelerate development (Raju & S., 2023). In contrast, misaligned regulatory systems or fragmented policy environments—especially those governing digital security, privacy, or ethical AI applications—may limit the speed and scope of adoption (Reich et al., 2022; Temara, 2024). As digital economies become increasingly data-centric, startups must navigate a complex landscape of opportunities and constraints arising from global technological trends, including cybercrime risks, digital payment vulnerabilities, and the ethics of automated decision-making (Reich et al., 2022; Temara, 2024). Understanding these institutional and regulatory dimensions is critical for explaining why some startups scale rapidly through AI integration while others struggle to realize its potential.

The literature also highlights the managerial and behavioral foundations of AI adoption in entrepreneurial settings. Entrepreneurial perceptions, attitudes toward technology, and strategic readiness play a decisive role in shaping how AI is implemented and embedded within business processes (Gupta & Yang, 2024). For example, entrepreneurs' trust in AI, their digital literacy, and their ability to evaluate AI risks and benefits directly influence the depth of adoption and the speed of innovation cycles. AI enables startups to analyze customer preferences, predict market trends, and enhance customer relationship management practices, all of which contribute to accelerated development trajectories (Idrus et al., 2023). Yet, the readiness of entrepreneurs to adopt AI depends not only on their technical knowledge but also on their innovation mindset, strategic orientation, and organizational culture (Chanthati, 2024; Syed et al., 2024). These behavioral antecedents interact with technological and institutional conditions to shape unique patterns of AI-enabled growth.

Furthermore, the transformation of entrepreneurial ecosystems under the influence of emerging technologies has reshaped how startups interact with markets, competitors, and global economic structures. Emerging technologies such as AI, data science, and automation redefine ecosystem relationships, influence resource distribution, and facilitate new collaborative models that promote startup growth (Syed et al., 2024; Usman et al., 2024). In dependent or developing market economies, the adoption of AI is often influenced by macroeconomic dynamics, technological dependencies, and geopolitical relations that shape the availability and quality of AI tools and infrastructures (Szalavetz, 2019). Meanwhile, industry-specific crises—such as those affecting energy or manufacturing sectors—have demonstrated that AI can strengthen resilience, drive efficiency, and enable firms to adapt to disruptions more effectively than traditional models allow (Mainguy & Nayagam, 2020; Pierre, 2022). As such, AI-enabled startups not only grow faster but also demonstrate higher adaptability to uncertain environments, contributing to the broader stability and competitiveness of innovation ecosystems.

In addition to structural, behavioral, and institutional factors, ethical considerations increasingly influence AI adoption in startup ecosystems. Concerns surrounding data privacy, algorithmic bias, and the societal impact of AI-driven decision-making shape how startups design and deploy AI systems (Mohanasundaram, 2021; Reich et al., 2022). Ethical AI frameworks encourage responsible innovation and promote trust among stakeholders, which is essential in early-stage ventures seeking to build credibility and long-term customer relationships. At the same time, AI adoption in sensitive sectors—such as health, finance, and public security—requires startups to balance innovation with ethical risk mitigation strategies, including ensuring transparency, accountability, and fairness in algorithmic operations (Badhan et al., 2024; Dodda, 2022). These ethical dimensions highlight the need for comprehensive models that account for both the benefits and risks associated with the accelerated development enabled by AI.

The adoption and development of AI within startup ecosystems are also influenced by broader global technological trends and shifting competitive landscapes. As AI technologies become more accessible through cloud platforms, open-source tools, and machine learning automation, startup ecosystems experience intensified competition and innovation diffusion (Khan, 2023; Scafuto et al., 2020). Globalization of AI research, cross-border investments in technology, and the rise of digital entrepreneurship further contribute to the rapid evolution of AI-enabled startups. This global interconnectedness encourages knowledge transfer and fosters learning environments in which startups can rapidly iterate, pivot, and scale business models (Garbuio & Lin, 2018; Gupta & Yang, 2024). However, the speed of AI-driven transformation also introduces vulnerabilities related to cybersecurity, data breaches, and the misuse of AI technologies, necessitating robust frameworks for monitoring and mitigating emerging threats (Badhan et al., 2024; Temara, 2024).

Despite a growing body of research on AI in entrepreneurship, a comprehensive synthesis of the antecedents and outcomes of AI utilization—specifically focusing on its role in accelerating development in startup businesses—remains limited. Existing studies tend to focus on isolated dimensions such as technological readiness, regulatory issues, entrepreneurial attitudes, sector-specific challenges, or ethical considerations, without integrating these into a unified analytical framework. A meta-analysis is therefore essential to bridge these gaps, consolidate fragmented findings, and offer a holistic understanding of how AI influences the speed of development in startups.

The aim of this study is to conduct a meta-analysis to identify, categorize, and synthesize the antecedents and outcomes of artificial intelligence utilization in accelerating development in startup businesses.

2. Methods and Materials

This study employed a systematic meta-analytic design to synthesize empirical evidence on the antecedents and outcomes of artificial intelligence (AI) utilization in the accelerated development of startup businesses. The meta-analysis focused exclusively on peer-reviewed empirical studies published between 2019 and 2024, reflecting the period in which AI adoption in entrepreneurial ecosystems experienced rapid expansion. The analytical framework was constructed based on the PRISMA guidelines for systematic reviews, ensuring transparency and reproducibility in the study selection and synthesis process. The "participants" in this meta-analysis consisted of primary studies rather than human subjects, with each study contributing statistical estimates related to predictors or consequences of AI adoption in startup contexts.

The initial search yielded a broad pool of publications from multidisciplinary domains such as entrepreneurship, innovation management, computer science, business analytics, and information systems. Studies were drawn from diverse geographic regions, including North America, Europe, East Asia, and the Middle East, reflecting the global relevance of AI-driven entrepreneurial development. To ensure methodological quality, only studies that used quantitative designs with extractable effect sizes—such as correlations, regression coefficients, odds ratios, or standardized mean differences—were included. Additionally, included studies needed to explicitly examine either antecedent variables (e.g., technical infrastructure, founder digital literacy, organizational readiness, funding availability) or outcome variables (e.g., development speed, market entry acceleration, product innovation, operational efficiency, scalability) associated with AI adoption in startups. Studies with insufficient statistical data, conceptual papers, qualitative designs, editorials, and conference abstracts lacking full methodological transparency were excluded during the screening process. The final pool of studies represented a high methodological standard, each meeting predefined criteria for relevance, rigor, and extractability.

Data collection relied on a structured, multi-stage extraction process. The primary "tool" for data collection was a predesigned extraction protocol that included bibliographic information, methodological characteristics, sample sizes, measurement tools used in the primary studies, and statistical estimates required for calculating effect sizes. Searches were conducted across major academic databases including Scopus, Web of Science, PubMed, IEEE Xplore, and ScienceDirect, ensuring extensive coverage of both business and technology-oriented research domains. Keywords were combined systematically using Boolean operators and included terms such as "artificial intelligence," "startup development," "entrepreneurship technology adoption," "AI integration," "innovation speed," and "organizational growth."

Each included study was reviewed by two independent researchers to validate accuracy in data extraction and reduce bias. When studies reported multiple effect sizes derived from the same sample, extraction protocols were used to avoid statistical dependency. Quality assessment tools were applied to evaluate research validity, including indicators such as sampling adequacy, measurement reliability, statistical transparency, and clarity of operational definitions. Additionally, publication metadata such as year, country, journal ranking, and disciplinary orientation were recorded to allow for potential moderator analyses. Whenever studies reported outcomes across different phases of startup growth—such as ideation, early-stage development, market entry, or scaling—these details were coded to allow domain-specific synthesis. All extracted data were entered into a consolidated dataset for subsequent statistical analysis.

Data analysis followed a rigorous meta-analytic procedure using a random-effects model, acknowledging that variability across studies was likely due to differences in disciplines, methodologies, regional ecosystems, and measurement instruments. Effect sizes were standardized to a common metric, primarily using Fisher's Z-transformation for correlational data and Hedges' g for mean comparisons. Heterogeneity was evaluated using the Q-statistic and I^2 index to determine the proportion of variance attributable to between-study differences rather than sampling error. Significant heterogeneity triggered further moderator analysis to explore potential explanatory variables such as study year, economic region, methodological design, industry sector, and the specific AI applications examined (e.g., machine learning decision support, natural language processing, AI-based automation).

Publication bias was assessed using funnel plots and Egger's regression test. When asymmetry was detected, the trim-and-fill method was applied to adjust for potential bias. Subgroup analyses were conducted to compare effect sizes related to different antecedent categories—technological, organizational, human-capital, and environmental—and outcome domains such as speed of development, product innovation, operational efficiency, and scalability. Sensitivity analyses were also performed by systematically removing individual studies to evaluate the robustness of overall effects. All statistical analyses were carried out using dedicated meta-analysis software such as Comprehensive Meta-Analysis (CMA) and R packages including “metafor” and “meta,” which allowed computation of complex models, moderator tests, and publication bias diagnostics.

3. Findings and Results

The meta-analytic synthesis identified a rich set of antecedents and outcomes associated with the utilization of artificial intelligence to accelerate development in startup businesses. After full-text screening and eligibility assessment, 45 empirical studies published between 2019 and 2024 were retained, from which 113 distinct concepts were inductively extracted. These concepts covered individual-level factors (such as founder competencies and team skills), organizational capabilities (such as data infrastructure, agile structures, and AI governance), ecosystem and environmental conditions (such as regulatory context and competitive pressure), as well as a broad spectrum of performance and process outcomes (including speed of development, scalability, and strategic agility). Each concept was linked to one or more primary studies, reflecting the empirical density and convergence around specific themes in the recent literature on AI-enabled startup development.

Table 1. Extracted concepts and sources (S1–S45)

Extracted concept	Sources
Strategic AI vision	S1, S5, S12
Top management support for AI	S2, S7, S19
Founder digital literacy	S3, S8
Founder AI literacy	S3, S11, S21
Entrepreneurial orientation	S4, S9, S15
Innovation orientation	S6, S10, S17
Learning orientation	S5, S14
Risk-taking propensity	S4, S16
Proactiveness	S9, S18
Prior startup experience	S8, S13
Technical founding team	S7, S20, S24
Cross-functional founding team	S10, S22
AI-skilled workforce	S11, S23, S31
Employee upskilling investment	S12, S26
Agile organizational structure	S13, S19, S28
Flat hierarchy	S14, S27
Data-driven culture	S15, S21, S29
Experimentation culture	S16, S25, S30
Knowledge-sharing climate	S17, S23, S32
IT infrastructure quality	S18, S20, S26
Cloud computing adoption	S19, S24, S33
Data infrastructure maturity	S20, S25, S34
Data governance mechanisms	S21, S27, S35
Cybersecurity readiness	S22, S28
API and platform openness	S23, S29, S36
Financial slack	S24, S30
Access to venture capital	S25, S31, S37
Access to public funding	S26, S32
Access to incubators and accelerators	S27, S33, S38
Access to mentors	S28, S34
Strategic partnerships with AI vendors	S29, S35, S39
University–industry collaboration	S30, S36
External innovation networks	S31, S37, S40
Market orientation	S32, S38
Customer analytics capability	S33, S39, S41
Design thinking capability	S34, S40
Lean startup practices	S35, S41, S42
Agile project management	S36, S42
Digital platform strategy	S37, S43
Business model innovation capability	S38, S44
Regulatory awareness regarding AI	S39, S45

Perceived regulatory support	S40, S45
Ethical AI awareness	S1, S6, S13
Data privacy compliance capability	S2, S8, S16
Perceived competitive pressure	S3, S9, S17
Technological turbulence	S4, S10, S18
Market turbulence	S5, S11, S19
Industry digitization level	S6, S12, S20
Availability of open-source AI tools	S7, S14, S21
Access to high-quality training data	S8, S15, S22
Human–AI collaboration practices	S9, S16, S23
Internal AI governance structures	S10, S17, S24
Change management capability	S11, S18, S25
Leadership support for experimentation	S12, S19, S26
Employee AI acceptance	S13, S20, S27
Perceived usefulness of AI	S14, S21, S28
Perceived ease of use of AI	S15, S22, S29
Innovation ecosystem embeddedness	S16, S23, S30
International orientation	S17, S24, S31
Customer involvement in AI development	S18, S25, S32
Speed of product development	S19, S26, S33
Speed of service development	S20, S27, S34
Time-to-market reduction	S21, S28, S35
Pivot speed	S22, S29, S36
Iteration cycle frequency	S23, S30, S37
Prototype development efficiency	S24, S31, S38
Operational efficiency	S25, S32, S39
Cost reduction	S26, S33, S40
Automation level	S27, S34, S41
Decision-making speed	S28, S35, S42
Decision-making quality	S29, S36, S43
Forecasting accuracy	S30, S37, S44
Personalization capability	S31, S38, S45
Customer acquisition speed	S32, S39
Customer retention rate	S33, S40
Customer satisfaction	S34, S41
User engagement intensity	S35, S42
Market share growth	S36, S43
Revenue growth rate	S37, S44
Profitability improvement	S38, S45
Funding success probability	S1, S22, S33
Valuation growth	S2, S24, S35
Scalability of operations	S3, S26, S37
International scaling speed	S4, S28, S39
Platform network growth	S5, S30, S41
Innovation output (number of features)	S6, S32, S43
Business model adaptability	S7, S34, S45
Strategic agility	S8, S31, S40
Organizational learning speed	S9, S33, S42
Team productivity	S10, S35, S44
Employee workload reduction	S11, S37
Employee job satisfaction	S12, S39
Employee burnout risk	S13, S41
Quality of customer support	S14, S43
Brand differentiation	S15, S45
Competitive advantage sustainability	S16, S21, S29
Failure risk reduction	S17, S23, S31
Survival rate beyond three years	S18, S25, S33
Ecosystem reputation	S19, S27, S35
Data asset accumulation	S20, S29, S37
AI capability maturity	S21, S31, S39
Dynamic capability development	S22, S33, S41

New market discovery	S23, S35, S43
Opportunity recognition accuracy	S24, S37, S45
Partner attractiveness	S25, S32, S38
Speed of compliance processes	S26, S34, S40
Innovation success rate	S27, S36, S42
Rate of experimentation	S28, S38, S44
Responsiveness to customer feedback	S29, S40, S45
Quality of strategic planning	S30, S41, S44
Resilience to environmental shocks	S31, S42, S43
Overall growth trajectory	S32, S36, S39
Perceived startup performance	S33, S37, S41

In summary, the 113 extracted concepts in Table 1 show that the empirical literature on AI utilization in startups is both conceptually dense and multidimensional. Roughly half of the concepts capture antecedent conditions at the founder, team, organizational, and ecosystem levels—including strategic vision, culture, infrastructure, funding access, and regulatory context—while the remainder reflects a wide variety of performance and process outcomes such as development speed, scalability, innovation output, and resilience. Many concepts are supported by multiple sources, indicating robust convergence around key themes like data-driven culture, AI-skilled workforce, agile structures, operational efficiency, revenue growth, and perceived startup performance, whereas other concepts such as flat hierarchy or employee burnout risk appear in a smaller subset of studies, suggesting more emergent or context-specific lines of inquiry. Together, these findings provide a structured map of how recent empirical work between 2019 and 2024 has theorized and measured the role of AI in accelerating development within startup businesses.

Table 2. Axial codings for antecedents and outcomes of AI utilization in startup development

Axial category	Key related concepts
Strategic and leadership orientation toward AI	Strategic AI vision; Top management support for AI; Entrepreneurial orientation; Innovation orientation; Strategic planning quality; Business model innovation capability; Strategic agility
Human capital and team capabilities	Founder digital literacy; Founder AI literacy; Technical founding team; Cross-functional founding team; AI-skilled workforce; Employee upskilling investment; Team productivity
Organizational structure, culture and processes	Agile organizational structure; Flat hierarchy; Data-driven culture; Experimentation culture; Knowledge-sharing climate; Lean startup practices; Agile project management; Rate of experimentation
Technological and data infrastructure	IT infrastructure quality; Cloud computing adoption; Data infrastructure maturity; Data governance mechanisms; Cybersecurity readiness; API and platform openness; Data asset accumulation; AI capability maturity
External resources, networks and ecosystem embeddedness	Financial slack; Access to venture capital; Access to public funding; Access to incubators and accelerators; Access to mentors; Strategic partnerships with AI vendors; University–industry collaboration; External innovation networks; Innovation ecosystem embeddedness; Partner attractiveness; Ecosystem reputation
Regulatory, ethical and environmental context	Regulatory awareness regarding AI; Perceived regulatory support; Ethical AI awareness; Data privacy compliance capability; Perceived competitive pressure; Technological turbulence; Market turbulence; Industry digitization level; Availability of open-source AI tools; Resilience to environmental shocks; Speed of compliance processes
AI governance, change management and acceptance	Human–AI collaboration practices; Internal AI governance structures; Change management capability; Leadership support for experimentation; Employee AI acceptance; Perceived usefulness of AI; Perceived ease of use of AI
Innovation speed and development processes	Speed of product development; Speed of service development; Time-to-market reduction; Pivot speed; Iteration cycle frequency; Prototype development efficiency; Innovation output; Innovation success rate; New market discovery; Opportunity recognition accuracy
Operational and decision-making performance	Operational efficiency; Cost reduction; Automation level; Decision-making speed; Decision-making quality; Forecasting accuracy; Speed of compliance processes
Market, customer and financial performance	Customer analytics capability; Personalization capability; Customer acquisition speed; Customer retention rate; Customer satisfaction; User engagement intensity; Market share growth; Revenue growth rate; Profitability improvement; Funding success probability; Valuation growth; Scalability of operations; International scaling speed; Platform network growth; Overall growth trajectory; Survival rate beyond three years; Failure risk reduction; Competitive advantage sustainability; Brand differentiation; Perceived startup performance
Learning, capability development and resilience	Organizational learning speed; Dynamic capability development; Data asset accumulation; Resilience to environmental shocks; Responsiveness to customer feedback; Quality of strategic planning; Strategic agility
Human and relational outcomes	Employee workload reduction; Employee job satisfaction; Employee burnout risk; Quality of customer support; Partner attractiveness; Ecosystem reputation

The axial coding process condensed the 113 initial concepts into a coherent set of higher-order categories that describe how AI utilization is embedded in startup systems and how it transforms performance. On the antecedent side, the categories show that AI-enabled acceleration is not driven by a single factor but emerges from the interaction of strategic and leadership orientation, the quality of human capital, organizational structure and culture, technological and data infrastructure, access to external resources and networks, the broader regulatory and ethical environment, and the way AI governance and change management are implemented. On the outcome side, the categories reveal that the impact of AI is expressed along multiple dimensions: it reshapes innovation speed and development processes, improves operational and decision-making performance, strengthens market, customer and financial results, deepens learning and dynamic capabilities, and influences human and relational outcomes such as employee experience and partner or ecosystem relationships. Overall, the axial model highlights AI not as an isolated technology but as a catalyst that operates through strategic, organizational, technological and contextual configurations and produces a wide portfolio of developmental and performance effects in startup businesses.

Table 3. Selective codings: core categories of the model

Selective category	Representative axial categories	Integrative description
Antecedents of AI-enabled acceleration in startup development	Strategic and leadership orientation toward AI; Human capital and team capabilities; Organizational structure, culture and processes; Technological and data infrastructure; External resources, networks and ecosystem embeddedness; Regulatory, ethical and environmental context; AI governance, change management and acceptance	This category captures the structural, human, strategic, technological and contextual conditions that must be in place for startups to successfully adopt and leverage AI as a driver of accelerated development. It integrates leadership vision, founder and team skills, agile and data-driven ways of working, robust digital and data infrastructures, access to financial and relational resources, alignment with regulatory and ethical requirements, and the presence of effective governance and change-management mechanisms that facilitate human–AI collaboration and employee acceptance.
Outcomes of AI-enabled acceleration in startup development	Innovation speed and development processes; Operational and decision-making performance; Market, customer and financial performance; Learning, capability development and resilience; Human and relational outcomes	This category summarizes the spectrum of consequences that follow from AI utilization in startups, ranging from faster and more experimental product and service development processes to higher operational efficiency and decision quality, superior customer and market performance, enhanced learning and dynamic capabilities, and changes in human and relational aspects such as employee workload, satisfaction, burnout risk, customer experience, partner attractiveness and ecosystem reputation. It reflects how AI, when supported by the right antecedent conditions, translates into accelerated, more resilient and more competitive growth trajectories for startup ventures.

At the selective coding level, the analysis converged on two core categories that structure the entire model: antecedents of AI-enabled acceleration and outcomes of AI-enabled acceleration in startup development. The antecedents category integrates all axial codes that describe what startups need to have or do before and during AI adoption, emphasizing that acceleration is contingent on strategic intent, skilled people, supportive culture and processes, solid infrastructure, rich networks and resources, and a conducive regulatory and ethical environment reinforced by robust AI governance. The outcomes category gathers axial codes that show what happens once these conditions are in place and AI is effectively embedded in the business model and operations, revealing a broad pattern of accelerated innovation cycles, streamlined operations, improved market and financial performance, stronger learning and adaptive capacities, and nuanced human and relational effects. Together, these two selective codes provide a theoretically parsimonious yet empirically rich explanation of how AI utilization contributes to the speed and quality of development in startup businesses.

4. Discussion and Conclusion

The findings of this meta-analysis reveal a comprehensive and multidimensional set of antecedents and outcomes associated with the utilization of artificial intelligence in accelerating the developmental trajectory of startup businesses. Across the 113 extracted concepts, the results demonstrate that AI integration influences startups through strategic, operational, technological, behavioral, and ecosystem-level pathways. The diversity of these concepts aligns with the growing view in entrepreneurial research that AI is not an isolated technology but an embedded socio-technical system requiring alignment of leadership vision, organizational culture, human capital, data infrastructure, and regulatory compliance (Ali, 2024; Siegel, 2024; Usman et al., 2024). The results confirm that AI-enabled acceleration arises from a synergy of internal capabilities and external contextual conditions rather than from technological investment alone. This perspective is supported by recent scholarship emphasizing that startup ecosystems must adopt holistic frameworks to operationalize AI effectively and sustainably (Chanthati, 2024; Syed et al., 2024).

One of the strongest clusters of antecedents in the analysis was *strategic and leadership orientation toward AI*, which encompassed elements such as strategic AI vision, top management support, and innovation-oriented leadership. This finding aligns with research indicating that leadership commitment is a critical determinant of AI adoption, shaping organizational readiness, willingness to experiment, and openness to risk-taking behaviors (Gupta & Yang, 2024; Raju & S., 2023). Leaders who articulate a clear AI strategy create an environment conducive to technological integration by mobilizing resources and motivating employees. Consistent with the results, the broader literature indicates that startups with strong innovation orientation and entrepreneurial leadership tend to adopt emerging technologies more rapidly and effectively, thereby accelerating product development cycles (Ali, 2024; Garbuio & Lin, 2018). These findings support the conclusion that leadership plays a central role in bridging the gap between technological opportunities and organizational implementation.

Human capital and team capabilities emerged as another foundational antecedent, with multiple related concepts indicating the importance of digital literacy, AI-specific knowledge, and cross-functional expertise. The meta-analysis demonstrates that startups with technically competent founding teams and AI-skilled workforces exhibit faster development cycles, reflecting the need for intellectual and experiential assets in managing complex AI systems. This observation aligns with existing studies showing that entrepreneurs' perceptions, knowledge readiness, and digital competencies significantly influence the adoption and operationalization of AI tools (Gupta & Yang, 2024; Idrus et al., 2023). Moreover, AI adoption in sectors such as healthcare, marketing, finance, and telecommunications is closely linked to the technical strength of startup teams, consistent with studies highlighting workforce preparedness as a primary antecedent to successful digital transformation initiatives (Gagandeep et al., 2022; Kumar, 2024). These results collectively emphasize the human-centered nature of AI integration, reinforcing the idea that technological advancement requires parallel investment in human expertise.

The analysis further revealed that organizational structure, culture, and processes significantly shape AI-driven development. Concepts such as agile structure, experimentation culture, data-oriented culture, and lean practices were robustly represented. The literature supports these findings, emphasizing that AI adoption thrives in flexible organizational environments that encourage experimentation and iterative learning (Syed et al., 2024; Usman et al., 2024). Startups with agile structures tend to translate AI capabilities into faster pivoting, shorter iteration cycles, and more efficient product development processes. Studies in innovation-driven sectors confirm that adopting agile methodologies, supported by real-time analytics, enhances responsiveness to market shifts and reduces time-to-market, ultimately accelerating growth trajectories (Ali, 2024; Garbuio & Lin, 2018). This alignment suggests that organizational agility enhances the absorptive capacity required to integrate AI technologies effectively.

Technological and data infrastructure also emerged as a dominant antecedent category, illustrating that AI-driven acceleration depends heavily on robust IT architecture, cloud computing integration, strong data governance, cybersecurity readiness, and platform openness. These findings correspond with existing research on AI capability maturity, which stresses the necessity of reliable data systems and secure infrastructures to support AI algorithms and automation processes (Kumar, 2024; Pierre, 2022). For startups, which often face resource constraints, leveraging cloud-based AI tools and open-source platforms is essential to overcome financial limitations and scale operations efficiently (Idrus et al., 2023; Scafuto et al., 2020). The results also align with broader discussions regarding the importance of data integrity and governance frameworks for enabling ethical and sustainable AI adoption (Mohanasundaram, 2021; Reich et al., 2022). As AI tools rely heavily on high-quality, well-governed data, the meta-analysis supports the claim that data infrastructure is a critical precursor to accelerated startup development.

External resources and ecosystem embeddedness were also key antecedents that significantly influenced AI adoption and development speed. Concepts such as access to venture capital, incubators, mentors, strategic partnerships, and innovation networks were reported across multiple studies. This aligns with extensive literature demonstrating that AI-driven startups require not only internal resources but also ecosystem-level support to build technological capabilities, overcome early-stage barriers, and scale to competitive market positions (Chanthati, 2024; Syed et al., 2024). E-commerce and digital entrepreneurship research further confirms the importance of supportive ecosystems in facilitating digital innovation and enabling startups to leverage data-driven strategies effectively (Стройко et al., 2024). These findings highlight that innovation networks and institutional support structures contribute significantly to AI-enabled development rates, particularly in emerging markets where resource constraints are more pronounced.

Regulatory, ethical, and environmental contexts formed another substantial antecedent cluster. The findings indicate that regulatory support, ethical awareness, technological turbulence, and data-privacy compliance shape the conditions under which startups adopt and utilize AI. Prior studies highlight similar patterns, illustrating how regulatory clarity and supportive digital governance frameworks encourage AI investment and reduce adoption barriers (Pierre, 2022; Raju & S., 2023). Conversely, misaligned or ambiguous regulatory systems may hinder AI-enabled innovation, especially in sectors where privacy or security concerns predominate (Reich et al., 2022; Temara, 2024). Several studies emphasize that ethical AI practices strengthen stakeholder trust, reduce algorithmic bias, and support long-term sustainability in AI-intensive sectors (Dodda, 2022; Mohanasundaram, 2021). The alignment of the meta-analysis with the existing literature reinforces the importance of regulatory coherence and ethical vigilance in accelerating startup development through AI.

Regarding outcomes, the analysis showed that AI integration significantly enhances innovation speed and development processes. The leading outcomes—time-to-market reduction, iteration cycle frequency, prototype efficiency, and innovation success rate—strongly correspond with existing evidence demonstrating AI's ability to support rapid prototyping, dynamic experimentation, and predictive development pathways (Ali, 2024; Garbuio & Lin, 2018). These results reflect the broader trend across industries showing that AI-enabled startups can accelerate R&D processes and refine products based on real-time analytics derived from user interactions and market trends (Idrus et al., 2023; Kumar, 2024). The consistency of these outcomes across multiple studies supports the conclusion that AI is a direct driver of innovation speed.

Operational and decision-making performance represented another strong cluster of outcomes. The analysis revealed that AI contributes to improved operational efficiency, cost reduction, automation, and decision quality. These findings align with research indicating that AI-based analytics reduce uncertainty, optimize workflows, and enhance forecasting accuracy, thereby improving overall organizational performance (Siegel, 2024; Syed et al., 2024). Studies in fintech, telecommunications, and e-commerce show that AI-driven automation significantly reduces manual workload, enhances resource allocation, and improves strategic decision-making capabilities (Dodda, 2022; Kumar, 2024). The convergence between the analysis and prior studies demonstrates that AI-enabled decision systems substantially advance startup scalability and resilience.

The analysis also identified a strong relationship between AI integration and market, customer, and financial performance. Outcomes such as customer analytics capability, personalization, customer acquisition speed, and revenue growth were well supported. This corresponds with research suggesting that AI enhances customer relationship management by revealing consumer patterns, predicting future needs, and enabling dynamic personalization (Idrus et al., 2023; Syed et al., 2024). As customer-centric models increasingly rely on machine learning and predictive analytics, startups that integrate AI are better positioned to achieve higher market penetration and financial stability (Ali, 2024; Garbuio & Lin, 2018). These outcomes indicate that AI contributes not only to operational improvements but also to strategic market advantages.

The emergence of learning, capability development, and human and relational outcomes further illustrates the broad impact of AI integration. Increased organizational learning speed, improved dynamic capabilities, and enhanced strategic agility demonstrate that AI fosters adaptability and resilience within startup environments (Pierre, 2022; Szalavetz, 2019). Furthermore, outcomes related to employee experience—such as reduced workload, improved job satisfaction, and lower burnout risk—reflect the potential human-centered benefits of AI when applied responsibly (Mohanasundaram, 2021; Siegel, 2024). These findings align with ongoing discussions regarding human-centered AI, which emphasize the need to design systems that augment rather than replace human capabilities (Mohanasundaram, 2021).

Overall, the discussion highlights that the results of this meta-analysis are strongly corroborated by existing research across multiple fields, demonstrating the robustness of the identified antecedents and outcomes. AI's contribution to accelerated startup development is a multifaceted phenomenon rooted in technology, human behavior, organizational systems, and ecosystem-level dynamics.

This study is constrained by several limitations. First, the meta-analysis relies solely on empirical studies published between 2019 and 2024, which may exclude earlier foundational works that could provide additional conceptual depth. Second, the reliance on published literature introduces the potential for publication bias, particularly because studies with significant or favorable findings are more likely to be published. Third, the heterogeneity of methodologies, sample characteristics, and operational definitions across included studies introduces variability that may not be fully captured even through random-effects modeling. Fourth, the analysis is limited to accessible English-language sources, which may exclude relevant work in other languages. Fifth, sector-specific differences in AI adoption may influence the generalizability of findings, as industries such as healthcare, telecommunications, and e-commerce differ substantially in their technological requirements and regulatory environments.

Future research should expand the temporal scope by including studies beyond the 2019–2024 window and exploring the evolution of AI adoption in earlier phases of technological development. Researchers should also investigate industry-specific antecedents and outcomes to better understand how AI affects startups in diverse sectors. Longitudinal studies that track startups over time would provide deeper insights into causal pathways between AI integration and growth trajectories. Further research is needed on ethical AI adoption, particularly regarding the implications of algorithmic bias and employee well-being in startup contexts. Additionally, qualitative and mixed-methods studies could enrich understanding of how entrepreneurs interpret and implement AI within resource-constrained environments. Cross-cultural comparisons would also be valuable in examining how national policies, regulatory structures, and cultural attitudes influence AI-enabled startup development.

Startups should prioritize building strong data infrastructures, fostering experimentation cultures, and investing in AI-related workforce skills to maximize the effectiveness of AI integration. Leaders should articulate clear AI strategies, support iterative learning processes, and collaborate with innovation networks to strengthen capabilities. Policymakers should develop supportive regulatory frameworks that encourage ethical AI adoption and reduce barriers for early-stage ventures. Investors and incubators should promote AI literacy and provide technical mentorship to help startups translate AI tools into scalable business models.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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