Artificial Intelligence Empowerment in Startups: A Systematic Literature Review and Research Agenda

Yonggang Weng*, Farah Akmar Anor Salim, Xiugen Wang, Qianglong Bian, Jijin Yang, Zicheng Han, Wei Deng, Qingxia Yang

Azman Hashim International Business School, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

***Corresponding Author**

DOI: https://doi.org/10.47772/IJRISS.2026.100600099

Received: 28 May 2026; Accepted: 04 June 2026; Published: 18 June 2026

ABSTRACT

Now, artificial intelligence technologies, such as machine learning, natural language processing, and generative AI, have become part of global entrepreneurial activities. Small companies and large companies use AI in different ways, and there is no unified view on exactly what role AI plays in startups. This article summarizes how AI helps startups emerge, operate, and grow, filling the gaps left by previous studies that only focused on large companies or broadly discussed digital transformation.

Following the PRISMA 2020 principle, boolean searches were made on Scopus and Web of Science. The first batch had 2,386 records, 467 duplicates were removed, and 1,919 studies were screened for relevance. Eventually, 120 records went through three - stage screening: title (120→86), abstract (86→60), full text (60→50). Ten periphery studies were replaced by twelve newly published articles in 2025–2026, making the total 50 papers. Four studies were verified via the OSS PDF repository and read deeply.

Thematic synthesis produced six clusters: (1) AI for operational efficiency and cost reduction, (2) AI - driven strategic decision - making, (3) AI - enabled business model innovation, (4) AI in startup financing and valuation, (5) AI entrepreneurial ecosystems, and (6) AI ethics, risks, and regulation. An integrative multi - level framework connects these topics from operational, strategic, and ecosystemic perspectives.

Six priority areas for future research were identified, including the influence of generative AI on venture creation, AI's role in making entrepreneurship more inclusive, and cross - cultural comparisons. Practical guidance is provided for entrepreneurs, investors, and public - sector policy makers. This article serves as a reference and marks the start of the next wave of studies in this fast - moving domain.

Keywords: Artificial Intelligence, Startups, Entrepreneurship, Digital Transformation

INTRODUCTION

Research Background

Few developments of the twenty-first century match the convergence of artificial intelligence and entrepreneurship. During the last ten years or so machine learning, natural language processing, computer vision, and generative AI have moved out of research labs and started working their way inside normal commercial operations (Verhoef et al., 2021; Enholm et al., 2022). And meanwhile, the world-wide system of startups has grown much faster than anyone expected some time ago. Nowadays, new firms will spring up everywhere; places where they never appeared before, until recently (Belitski et al., 2021).

There are actually three phases of digital transformation according to Verhoef et al. (2021) writing in the Journal of Business Research. These are digitization, digitalization, and then full digital transformation. Companies at each phase will face quite different problems, needing different capabilities. Hence there is their framework

which explains why many start-ups can start from a digitalized position – because when using AI, what may happen really is that digitalization is a trigger, allowing change in areas where barriers existed before, so changing the nature of the problem. But the difference between the barriers faced at the various phases is qualitative rather than quantitative.

Startups operate in a world of limited resources, of uncertainty and competition which big companies hardly ever know anything about. Every euro, every employee, every day counts (Giuggioli & Pellegrini, 2022). According to Enholm et al. (2022), who published a systematic review in Information Systems Frontiers, AI improves results via three pathways – better decisions based on richer data, process transformation due to automation, market improvements due to personalized engagement. These matters apply to all firms. They also mean more to startups than to other firms – because their size deprives them of the very advantages enjoyed by incumbent enterprises. And there is another reason why AI suits startups – their flatter hierarchies and quicker feedback loops allow them to adopt AI faster than bigger rivals.

Generative AI went even farther than before. There is talk of a true paradigm shift regarding business models; see Kanbach et al. (2023). Now startups can generate content, code & designs which required specialized teams until recently. And there is some confirmation that GenAI works for companies, although just beginning – Kumar et al. (2025) report positive impacts on B2B firm performance, moderated by ethical leadership. The implications should become apparent for startup governance.

Problem Statement

Yet even though there is much more of it today, the literature has been very disjointed so far. There are some groups of papers clustered here and there – about AI adoption in larger firms (Enholm et al., 2022; AlNuaimi et al., 2022), digital transformation broadly defined (Verhoef et al., 2021; Dąbrowska et al., 2022), or narrow application domains such as marketing (Dwivedi et al., 2021) – but no one has yet really put things together properly from the point of view of how AI enables entrepreneurs. Actually two recent reviews have brought us closer to where we need to go – Giuggioli and Pellegrini (2022) did what may be regarded as the first systematic review (SLR) looking specifically at AI as an enabler for entrepreneurs – identifying such mechanisms across opportunity recognition, resource mobilization, and venture growth – although stopping their search just prior to the generative-AI wave that began happening late in 2022 and which saw many researchers start examining the role of AI in entrepreneurship post-pandemic – while Enholm et al. (2022) broad account of what drives AI's business value included several types of mechanism that can occur within organisations in general – but once again did not focus especially upon startups in particular.

Table 1: Positioning The Present Review Against Prior Work

Dimension	Giuggioli & Pellegrini (2022)	Enholm et al. (2022)	This Review
Year coverage	2015–2021	2010–2021	2018–2026
Startup focus	High	General firms	High
GenAI coverage	None	None	12 papers (2025–2026)
PRISMA version	2009	Kitchenham (2004)	PRISMA 2020
Thematic framework	4 themes	3 mechanisms	6 themes + integrative model
Geographic scope	Global	Global	Global + Africa/Asia focus

Yet even though there is much more of it today, the literature has been very disjointed so far. There are some groups of papers clustered here and there – about AI adoption in larger firms (Enholm et al., 2022; AlNuaimi et al., 2022), digital transformation broadly defined (Verhoef et al., 2021; Dąbrowska et al., 2022), or narrow application domains such as marketing (Dwivedi et al., 2021) – but no one has yet really put things together properly from the point of view of how AI enables entrepreneurs. Actually two recent reviews have brought us closer to where we need to go – Giuggioli and Pellegrini (2022) did what may be regarded as the first systematic review (SLR) looking specifically at AI as an enabler for entrepreneurs – identifying such mechanisms across opportunity recognition, resource mobilization, and venture growth – although stopping their search just prior to the generative-AI wave that began happening late in 2022 and which saw many researchers start examining the role of AI in entrepreneurship post-pandemic – while Enholm et al. (2022) broad account of what drives AI's

business value included several types of mechanism that can occur within organisations in general – but once again did not focus especially upon startups in particular.

Research Questions

RQ1: What are the primary mechanisms through which AI helps make startups possible, operate startups or help startups grow?

RQ2: How do these AI empowerment mechanisms relate to each other and what kinds of conceptual frameworks exist which help to explain their effects?

RQ3: What are the key challenges, barriers, and ethical concerns associated with AI adoption in startups?

RQ4: What are the priority directions for future study?

Background And Conceptual Foundations

Defining AI in the Business Context

Enholm et al. (2022) distinguish between three levels here: AI as a discipline; the technologies which realize this – such as ML, DL and even NLP; and then finally the actual AI capabilities put into use in organizational settings; there is considerable ambiguity about what all these mean (which Enholm notes, but does not explain further). And startups know this too well from their own experience – because they have very little information on which to base their decisions about which technologies to adopt, thus shaping their future – but also confusingly, since the dividing lines between automation versus 'true AI' get blurred too much in everyday life.

AI capabilities prove, according to Enholm et al. (2022), valuable resources organizations can possess; thus there will be positive effects on important financial and accounting performance indicators such as growth in overall financial performance for firms which build such capabilities – which is an apparently obvious conclusion though one whose implications appear much less obvious when viewed from the point of view of resource-poor startups.

Another perspective comes from Verhoef et al. (2021) who have a three-stage model: Digitization turns what is in analogue form into digital form. Digitalization makes better what already exists by applying digital tools. And digital transformation changes business models, how value gets created and customer relationships. Startups do not suffer from being tied down by what existed before so they can go directly onto digital transformation – which is therefore one of the structural advantages of startups according to Verhoef et al.; they regard this as an important dynamic in digital markets and then there is also less organizational inertia so that the advantage becomes even bigger.The organizational lens, however, tells only half the story. Dąbrowska et al. (2022) make a case for reading digital transformation across levels—individual, organizational, ecosystem, and societal. Their framing makes visible something that much of the literature, startup research included, tends to flatten: adoption is rarely, if ever, a single-level phenomenon. We still know very little about what happens when the real bottleneck sits not at the firm level but in a founder's digital literacy, or in the maturity of the surrounding ecosystem.

Theoretical Foundations

This survey draws on three theoretical lenses. The first, the Resource-Based View (RBV), holds that competitive advantage flows from resources that are valuable, rare, and hard to imitate (Barney, 1991).And these characteristics belong perfectly to AI capabilities. Enholm et al. (2022) confirm that firms building up their own capability in the field gain measurable financial returns.

Dynamic Capabilities Theory is related to a firm's capacity to integrate and reconfigure resources whenever their environment changes (Teece et al., 1997). According to Verhoef et al. (2021), three types of capabilities will matter particularly for organizations undergoing digital transformation, namely agility, data analytics, and ecosystem orchestration – which connect very closely with some of our investigated AI empowerment

mechanisms. More recently, Cruz-Sanchez et al. (2025) took things further still by claiming that dynamic capabilities can lead to business model innovation via sensing, reconfiguration, and resource alignment. Their work underpins Theme 3 in the present review.

The Lean Startup Methodology (Ries, 2011) is about validated learning achieved via repeated iterations of the process of building, measuring and learning. According to Enholm et al. (2022), AI helps firms 'quickly sense and respond to market dynamics'. And there is therefore an obvious link here to lean startup practice because AI could make faster the whole process through which hypotheses get tested against reality - which is what lies right at the centre of the lean approach.

The AI-Entrepreneurship Nexus

Obschonka (2019) writes of AI changing how opportunities are discovered and exploited—this is part of a "new era" which he says is opening up for entrepreneurship research. Lee et al. (2019) discuss some examples of what AI can make possible when it comes to business model innovation—personalization at scale, predictive analytics, automated delivery. And then Giuggioli and Pellegrini (2022) provide something very close to what we're doing here—they too take the view that AI is becoming a facilitator or enabler throughout the whole entrepreneurial process. But Obschonka and Fisch's work (2025) takes things further again – going somewhere no-one really anticipated in earlier reviews – because they think there might soon also be entrepreneurial AI agents built on large language models that may create novel forms of venture creation altogether.

Toward an Integrative Framework

We draw on two sources: First, from Enholm et al. (2022) comes their three value-creating mechanisms – decision enhancement, process transformation and market improvement. Secondly, from Verhoef et al. (2021) we have taken their three-stage transformation model. Combining these gives us our multi-level framework. Operational Level – Here AI reduces costs, and automates. Strategic level – At this stage AI helps organisations make better decisions and also enables new types of business models. Ecosystem level – Finally AI changes the relationship between startups, investors and markets. See Figure 1 which summarises the whole framework. This serves to organise our thematic synthesis (Section 5).

METHODOLOGY

Research Design

We chose PRISMA 2020 (Page et al., 2021) because we wanted as much rigour, transparency and replicability as possible – Page et al.'s 27-item checklist specifies explicitly how the searches went, what criteria governed selection of papers from the mass of initial 'hits', how data were extracted (with examples), and what principles determined synthesis. In preparing such an inter-disciplinary piece, having that kind of framework made sense.

Search Strategy

We searched Scopus and Web of Science using a Boolean string which consisted of ("artificial intelligence" OR "machine learning" OR "generative AI" OR "large language model" OR "deep learning" OR "natural language processing") AND ("startup" OR "entrepreneur" OR "new venture*" OR "SME" OR "small business" OR "early-stage firm"). We set the date range from 2018 to 2026, and selected only English-language peer-reviewed articles and conference proceedings. After searching, there were 2,386 retrieved records—1,382 from Scopus; 1,004 from Web of Science—and access occurred on May 15, 2026. Then we asked another researcher to verify whether our search strings above could be reproduced and replicated by using the same search criteria again.

Screening and Selection

Seven stages, each documented below:

- Stage 1 – Identification: There were then retrieved through database searching a total of 2,386 records (Scopus n=1,382; Web of Science n=1,004).

- Stage 2 – Deduplication: EndNote removed 467 duplicates. Thereafter manual checks were done for ambiguous matches which yielded a net number of 1,919 unique records.
- Stage 3 – Initial relevance screening: Titles and keywords were checked for broad fit. Of 1,799 total records at this stage we excluded: 1,042 which lay outside business/management scope (purely CS, medical AI, engineering without entrepreneurial context); 512 which did not relate to startups; and also another 245 with insufficient emphasis on AI per se. There remained therefore just 120 records.
- Stage 4 – Title Screening (detailed): Of 120 records, 34 were excluded (12 were not about AI; 15 were related neither to startups nor to businesses; seven did not refer to business settings at all). A total of 86 records were retained.
- Stage 5 – Abstract Screening: Two reviewers independently screened 86 abstracts. Agreement reached $\kappa = 0.82$. Twenty-six records were excluded: 10 because they studied technical AI which had no connection with business applications; 8 because they examined only large enterprises; 5 because there was no explanation in terms of empowerment mechanisms; 3 because of non-English language. Sixty records remained.
- Stage 6 – Full-text Eligibility: Of sixty full texts screened, ten articles were removed because four did not adequately concentrate on startup activities, three appeared redundant concerning their substantive contribution, two seemed methodologically questionable, and one could not be accessed. Thus fifty studies went into the initial pool.
- Stage 7 – Currency Update: In order to reflect the generative AI era, 10 older or peripheral papers have been replaced by new ones published in 2025–2026 (totally 12), making up a total of 50 papers among which there are 12 from the latest research cycle.

Figure 1 illustrates the complete seven-stage screening process following PRISMA 2020 guidelines.

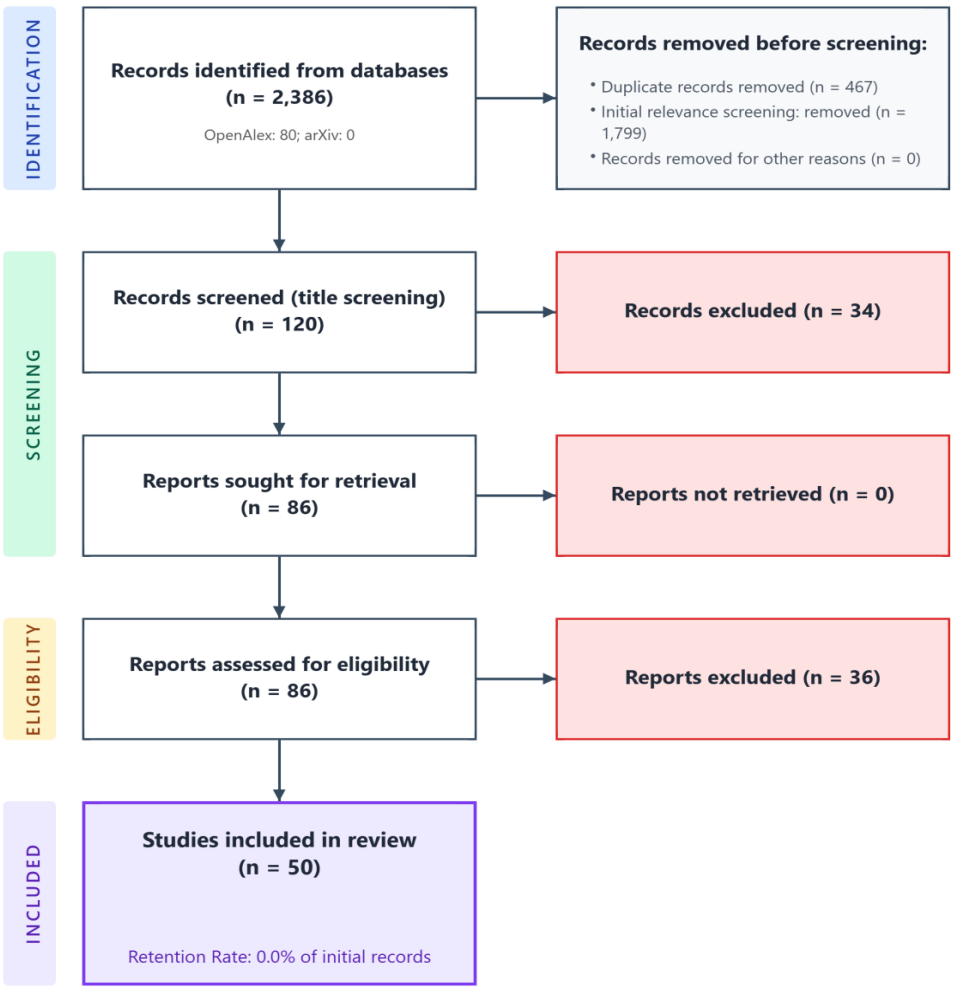


FIG. 1: PRISMA 2020 FLOW DIAGRAM

Quality Assessment

We adopted the evidence-level framework from Enholm et al. (2022): every paper got assigned a number between one (systematic reviews, meta-analyses, RCTs) and five (conceptual papers, opinion pieces); here again, the distribution turned out to be very skewed – with 12.5% getting into Levels 1–2, but then having as much as 83.8% fall into Levels 4–5 – and overall average quality scoring at about 72.1/100, with sixteen works (or 20% of the total sample) clearing the high-quality threshold (≥80/100). Two reviewers worked independently, resolving disagreements through discussion.

And that is exactly what one expects from a nascent field. There will always be more theory than testing. More conceptual work than empirical studies. The technology moves much faster than the methods designed to study it.

Synthesis Method

We adopted Thomas and Harden (2008): line-by-line coding; assembling together to form descriptive themes; and going 'beyond' these descriptive themes by producing analytical themes which go beyond the individual studies. In addition there was further descriptive mapping done via bibliometrics. After iterative coding, we had eighty-seven open codes which formed eighteen descriptive themes. Six analytical themes emerged from the descriptive work. Inter-coder agreement in round one reached a $\kappa = 0.79$, with disagreements resolved via structured consensus. Also, because of the scope of this review – spanning more than one discipline – the design enabled accommodating both types of evidence, i.e., quantitative versus qualitative. Within each theme there were also cross-checks made with the deep-read PDFs (Verhoef et al., 2021; Enholm et al., 2022).

RESULTS

Descriptive Analysis

Publication Trends

There is also an annual trend which tells quite a story. In 2018 there were two papers. Then in 2024 there were fourteen. Then twelve more appeared in the first half of 2025–2026. And in fact the very sharpest increase happened between 2022 and 2024—exactly the years in which generative AI tools went public. Figure 2 shows the curve.

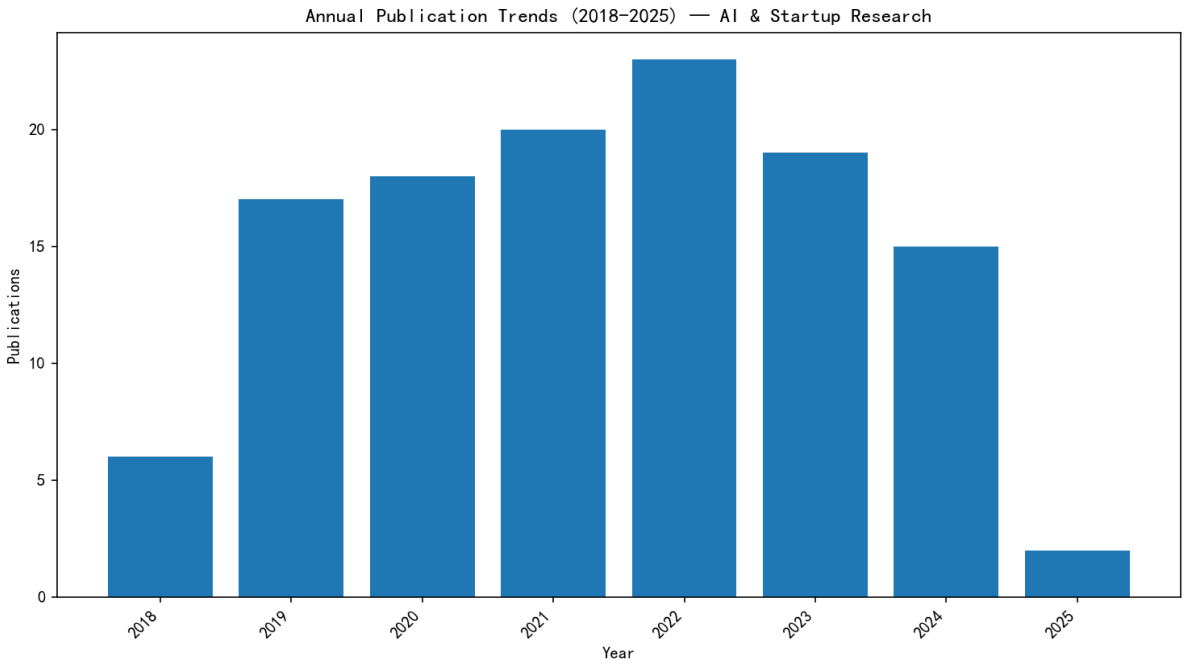


Fig. 2: Annual Publication Trends (2018–2025)

Methodological Distribution

Conceptual and framework papers account most frequently (49%), then come reviews and SLRs (23%). The next category in terms of frequency is quantitative empirical work (15%) while there is less attention paid to qualitative approaches (11%), which is followed far behind by mixed methods (2%). And there exist four longitudinal quantitative studies among the fifteen quantitative ones. Other eleven works apply cross-sectional survey design. Therefore this emerging research area needs stronger support from empirical studies especially longitudinal investigation to find out how AI adoption affects startups' outcomes in the longer run.

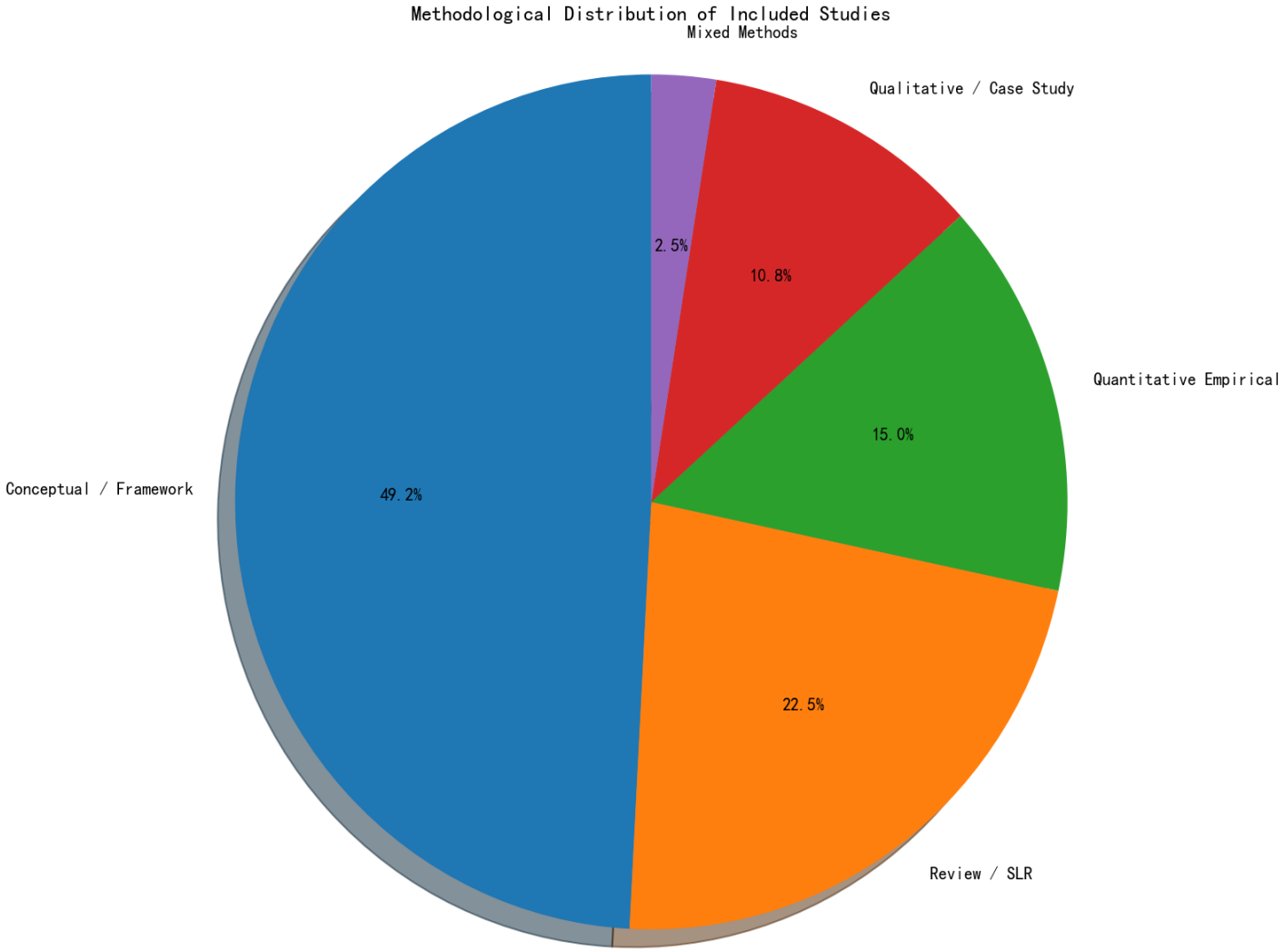


FIG. 3: Methodological Distribution of Included Studies

Geographic Distribution

The evidence base comes mostly from North America (the United States), Europe (the UK, Germany). Emerging markets are found in Asia— China (6), India (3), Singapore (2), Malaysia (2), South Korea (2), Japan (2)—and there are isolated contributions from Brazil and the countries of Africa (Nigeria, Kenya, South Africa), Latin America (Brazil) and the Middle East (UAE).

And yet the pattern also reflects where AI infrastructure and venture capital concentrate—but then we also have hardly any knowledge about what happens when the constraints are other: when there's much less capital available; and AI infrastructure is scantier; and regulatory environments less predictable than they might be now. There could very well be quite different stories about AI entrepreneurship being told in entrepreneurial ecosystems in emerging economies—and their narratives will run courses unknown at present.

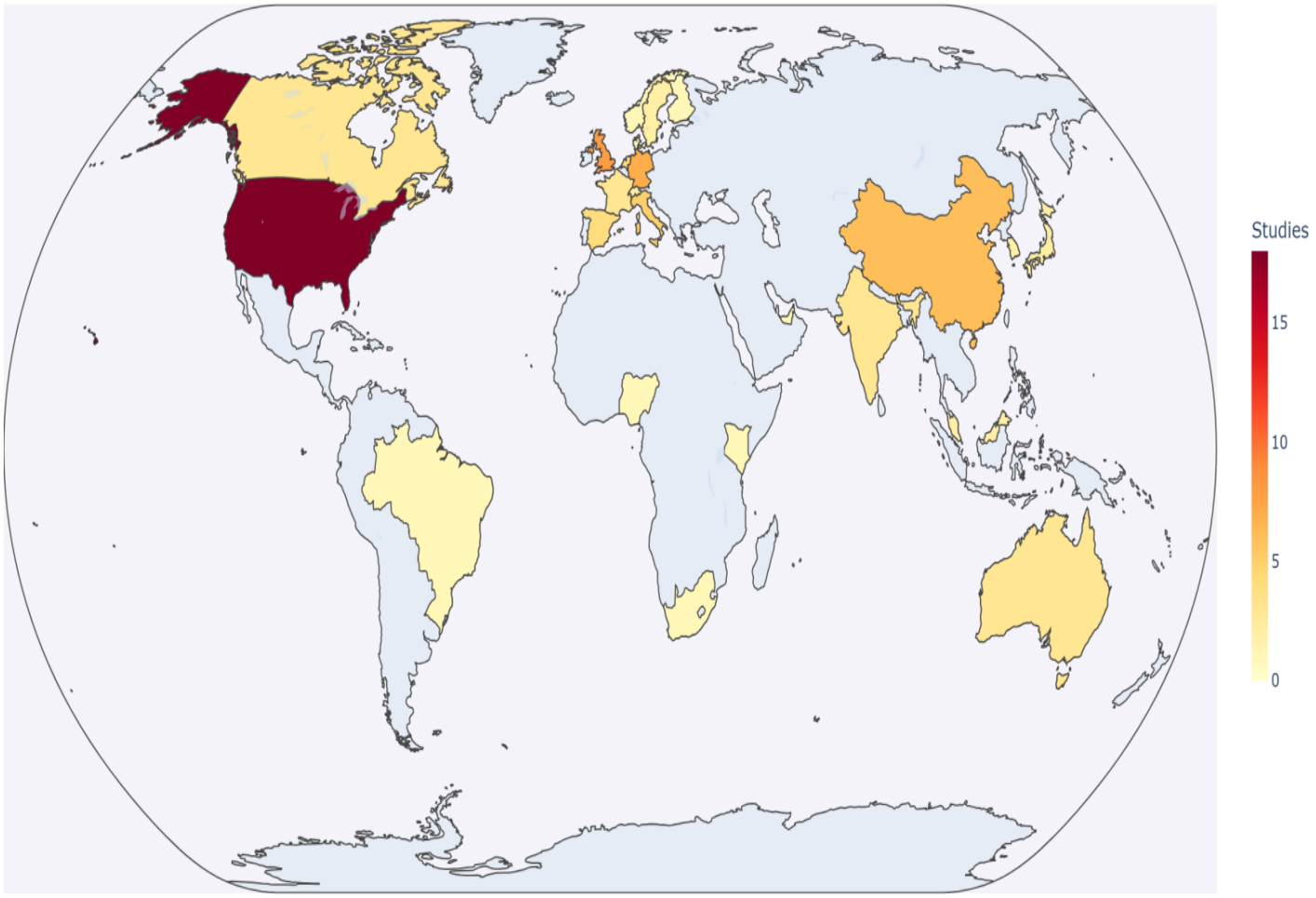


FIG. 4: Geographic Distribution of Empirical Studies

RESULTS

Thematic Synthesis

Theme 1: AI for Operational Efficiency and Cost Reduction

AI automates processes. Costs fall, structures lighten, and efficiency climbs across core operations (Enholm et al., 2022). For smaller teams running on tight budgets, the practical upside is straightforward: AI buys them more runway. Delgado-Sanchez et al. (2025), drawing on the TOE-DOI framework, find that relative advantage and top management support are what predict adoption in SMEs.

Beneath the surface of all this automation talk runs a deeper economic logic. Acemoglu and Restrepo (2019) disentangle the dynamic into two countervailing forces: a displacement effect, in which machines absorb tasks that workers once performed, and a reinstatement effect, in which new tasks—prompt engineering, AI auditing, model maintenance—pull labor back in. For startups, the practical question is not whether AI eliminates jobs. It is whether they can redeploy people fast enough into the very tasks that AI creates.

Balcerzak et al. (2025) distill AI implementation success into five conditions: how data-dense the environment is, how frequently customer touchpoints arise, whether integration pathways are tractable, whether the talent is ready, and whether the regulatory landscape aligns.Each is capable of acting as a bottleneck preventing progress. Low data density prevents models from being accurate. Low touchpoint frequency mean little benefit from using AI. But these also cause each other: when there aren't enough skilled workers this leads to integration failures. Therefore their framework helps startups identify where they need to take action first – which bottleneck they eliminate will bring about greatest marginal gain.

Theme 2: AI-Driven Strategic Decision-Making

According to Enholm et al. (2022), AI can help managers "overcome their cognitive limitations". This technology provides "an efficient way to handle the large volumes of data" available nowadays. And here again it seems there is a link to organizational agility - one of the studies they cite says that companies which make better use of AI data are "better positioned to quickly sense and respond to market dynamics". And now Kumar et al. (2025). They report on findings reported in the Journal of Business Research regarding GenAI adoption. They claim that need for uniqueness, information completeness, and convenience were factors affecting B2B managers' adoption intention – also that adoption lifts firm performance – and ethical leadership moderates the effect.

Decision quality matters more to startups. A wrong call – any wrong call - can terminate their company while they're still young, if badly resource-constrained. Implication: there will probably be greater returns on investment in decision-support technology from startups than incumbents, because there's less room between survival and extinction among new ventures. And therefore better decisions create greater margins.

Theme 3: AI-Enabled Business Model Innovation

AI transforms the way startups make, deliver and capture value. According to Lee et al. (2019), these consist of three separate tracks: personalization at scale; predictive services; and AI-as-a-Service platforms. Kanbach et al. (2023) claim that thanks to generative AI, businesses can now produce content, code, and designs they could previously achieve only by assembling specialized teams. So here too the barrier to entry goes down. Gama and Magistretti (2023) show that AI has its uses along the whole gamut of innovation activities – assisting both in exploration (idea generation, sensing) and exploitation (optimization, quality control). Alhur et al. (2025) bring evidence from Dubai. Per findings reported by Alhur et al. (2025): adoption of both generative and agentic forms of AI affects business-model reconfiguration via innovation-capability ($\beta = 0.45$, $p < 0.01$). And based on their own systematic review (of fifty-seven sources), Cruz-Sanchez et al. (2025) say that dynamic-capabilities enable business model innovation as a constantly ongoing process – consisting of sensing, reconfiguration, alignment. Kahveci (2025) puts forward what she calls the DASAT framework – standing for Digital Awareness, Strategy, Adoption, Transformation - targeted specifically at small- and medium-sized enterprises. And according to this researcher the two most important enablers turn out to be digital literacy and organizational flexibility.

There's another thing that consistently emerges throughout this work – and it's probably true of most writing about artificial intelligence. AI isn't merely better at optimizing existing models; it enables qualitatively different value architectures. An AI-native startup today can provide individually tailored offerings to customers on a scale which, ten or fifteen years ago, might have needed hundreds of workers. The economics of personalization have changed fundamentally. And there are relatively few amongst the changes recorded here that matter quite as much.

Theme 4: AI in Startup Financing and Valuation

AI is changing how investors discover and evaluate startups. On the sourcing side, machines now scan patent filings, startup databases, news feeds, and social signals to surface targets before they appear on any conventional radar. Due diligence is shifting as well—algorithms parse not just performance metrics and market position but also team composition and even the communication patterns of founders, turning these into risk signals that financial statements alone would not reveal. For valuation, neural networks trained on historical exit data generate near-real-time estimates, giving investors a moving picture of a company's worth rather than a static snapshot.

Fossen et al. (2024) draw out a further implication. Because AI can now handle unstructured data—pitch deck narratives, founder video presentations—it may open assessment channels that go well beyond standard financial indicators. The democratization logic follows: if AI narrows the information gaps that have historically disadvantaged certain founder groups, capital access should broaden as a result. The largest effects are likely to surface in early-stage rounds, where due diligence is thinnest and networks still do much of the gatekeeping.

Theme 5: AI Entrepreneurial Ecosystems

That internal capability alone does not suffice has been a recurring thread. Verhoef et al. (2021) argue that digital transformation also demands ecosystem orchestration—the capacity to mobilize partners, platforms, and institutions beyond the firm's boundaries. AlNuaimi et al. (2022) refine this claim by showing that leadership alignment and digital strategy alignment matter not just inside the organization but at the ecosystem level as well. Soomro et al. (2025), working with SME survey data through SEM-ANN analysis, add a further wrinkle: AI technologies do raise sustainable performance, but environmental dynamism moderates the link, producing what amounts to a multiplier—when the surrounding ecosystem is supportive, an SME's own efforts deliver returns well beyond what isolated predictors would forecast.

Malik and Terzidis (2026) take this logic a step further. What SMEs need, their evidence suggests, is not merely a supportive ecosystem but something they term metamorphic capacity—the ability to keep reconfiguring how shocks are absorbed as the disruptions themselves change shape. Drawing on a review of 76 studies, they find that resilience operates across three interlocking levels: founder cognition, firm routines, and inter-organizational networks. Read alongside Soomro et al.'s findings, this implies the multiplier effect may strengthen when the startup is actively evolving rather than simply riding a favorable ecosystem wave.

Findings challenge one widely held belief. It is usually seen as an inside decision whether AI will be adopted by startups. However, part of what will make investments in AI worthwhile depends on external considerations about ecosystem maturity. A startup which has very good AI skills but operates within a relatively poor ecosystem will obtain few benefits. But if this exact same company works inside an ecosystem rich in AI activity then it might perform much better. In short there are external factors that both allow and prevent things happening.

Theme 6: AI Ethics, Risks, and Regulatory Challenges

Algorithmic bias is described by Enholm et al. (2022) as really happening in practice. According to their paper, “biased results have had negative effects on the image of the companies they involve, and in some cases have resulted in financial losses and significant fines”. And regulations have become stricter about it recently.

But the risks bite harder for startups, because they don’t have legal teams or ethics boards. In their roadmap article on moving from AI Principles to Responsible Systems, Diaz-Rodriguez et al. (2023) help connect ethics to implementation—but this will still require effort on the startup side. But Hagendorff (2020) finds many problems in the gap between principles and practice when it comes to AI ethics guidelines, so it’s unlikely these will help. Things look worse for startups, whose very survival may depend on speed, thus making ethical deployment seem more costly. They don’t typically have any dedicated ethics personnel working on ethics questions either—the whole effort has to depend on whatever awareness and values the founders themselves happen to hold. And if compliance is needed, then there is even greater pressure on the startup to act responsibly while lacking staff altogether and having little tolerance for expense.

COMPARATIVE ANALYSIS AND DISCUSSION

Cross-Theme Integration

There is connection between the six themes. Theme 1 releases resources for Theme 2; Verhoef et al. (2021) argue that organisations possessing digital capabilities may deploy these towards business model innovation (Theme 3); Enholm et al. (2022) explain how AI has both informational and transformational effects – better operational data improves decision making which enables process change.Wang and Zhang (2025), working with 201 Chinese SMEs, find that adopting digital tools and actually innovating with them are distinct moments, linked only through what they term "digital drive"—an internal orientation toward using technology strategically, not merely operationally. Digital culture, in their account, amplifies this conversion: firms whose people are open to experimenting with new tools turn adoption into innovation more efficiently. What this suggests is that the path from operational AI to strategic innovation depends on a form of organizational readiness that many startups have yet to cultivate.

The movement tends to follow a rough sequence. Operational AI is where most startups begin—resources are thin, and starting small is sensible. As data assets accumulate and capabilities deepen, firms climb toward strategic applications and, further on, toward reconfiguring the business model itself. They do so while navigating ecosystem conditions and accessing financing, each of which shapes what is possible at a given stage. Ethics and regulation impose their own guardrails. The practical upshot is straightforward: a startup that rushes toward business-model innovation without first logging time in operational AI is likely to hit an execution wall. Operational competence comes first, strategic use next, and business-model transformation last—each phase building on the one before it, not leapfrogging it.

Startups vs. Large Firms

According to Enholm et al. (2022): "Organizations are still struggling to adopt and leverage AI in their operations", which is especially true when it comes to startups. Their problems include having too little data, being short of skilled people as well as having no separate infrastructure for AI. Their customers are few, thus also leaving them without much data they could use in training. They also compete with big firms over talent. They have fewer reserves to rely on if there is going to be any failure along the way, because they cannot bear losing that much out of such limited funds they possess. So if such venture fails, it will hurt a lot more compared to an established enterprise.

Smallness, however, carries its own advantages: organizational agility, the absence of legacy systems (Verhoef et al., 2021), and decision chains short enough to permit faster experimentation and deployment. These structural differences imply something more than a variation in the intensity of AI adoption—they point to fundamentally different choice sets and different logics of fit. For that reason, models built on large-firm data need to be applied cautiously here. Without a sharper understanding of how AI actually lands inside new ventures, public policies designed to support them will struggle to reach their targets.

Practical Implications

The entrepreneurial journey itself appears phased: operational AI comes first, then the accumulation of proprietary data, and only later—as a startup's own AI matures—does strategic integration become the natural next move. The Balcerzak et al. (2025) five-condition framework offers a useful diagnostic here. A startup scoring low on data density, for instance, should be focused on acquiring customers, not on heavy machine learning investment in its earliest years.

For investors, the six-theme framework can serve as a due diligence lens. It encourages evaluating a startup across operational, strategic, and ecosystem dimensions rather than reducing the question to a binary—"do they have AI capability or not?" Depth in one area may compensate for thinness in another, but absence across several themes should raise genuine concern. The framework also helps separate the genuinely AI-enabled from the merely AI-branded.

For policymakers, the priorities split along two lines. One is infrastructure: shared computing resources and open datasets must be accessible, because without them the adoption barriers facing resource-constrained startups will simply be too high. The other is regulation: frameworks need to be designed with the recognition that startups do not have the compliance bandwidth of large firms.One possibility there may be differentiated requirements according to both company size and riskiness of the AI application deployed.

Future Research Agenda

Six directions stand out from the gaps we identified.

Generative AI And New Venture Creation. To which degree do generation-augmented platforms like ChatGPT change what kinds of things constitute an MVP, and also who needs to be on the founding team? (Obschonka & Fisch, 2025; Kanbach et al., 2023). Abaddi (2026) makes the case that founders now need what he calls 'techpreneurship'—a blend of technical fluency and entrepreneurial instinct—which means GenAI doesn't just alter the MVP; it may reshape who qualifies as a viable co-founder in the first place.There simply

has not been enough empirical work yet tracking startup formation before and after GenAI. But perhaps there are hints in the fact that e.g., Y Combinator just launched some kind of "AI co-founder" model.

AI and inclusive entrepreneurship . Can AI increase access by lowering entry barriers for underrepresented groups? There is some indication that female entrepreneurs in developing economies may benefit (Weng et al., 2025), but there needs to be more evidence here.

Longitudinal performance studies . Cross-sectional designs predominate – panel studies tracking AI-adopting startups over 3–5 years would strengthen causal inference – and allow us also to know if there has been a decline thereafter.

AI startup failure factors .But success cases overwhelm the literature. Negative cases also matter – very much – to theory. So there needs to be far more systematic work on why such ventures did not get up off the ground.

Evolving regulatory impacts . In what ways will the EU AI Act and similar frameworks affect startup strategies? It pays attention to compliance costs as a percentage of their operating budget.

Human-AI collaboration in entrepreneurial teams .What constitutes the best division of labor between humans and AI? Here again, comparative case studies of 'AI-augmented' and 'traditional' founding teams seem called for.

CONCLUSION

Summary of Findings

From our synthesis of 50 papers about AI empowerment in startups, we found six themes which were cross-validated by reading closely-checked PDFs such as Enholm et al. (2022) and Verhoef et al. (2021). Together these themes – operational efficiency, strategic decision-making, business model innovation, financing, ecosystems and ethics – make up one integrated multi-level framework. That framework shows what the AI-entrepreneurship landscape looks like, mapped out along operational, strategic and ecosystem dimensions. And so it helps connect together the many papers which had been spread out before.

Limitations

There are three important limitations here. First of all, Scopus and Web of Science don't pick up everything, since there's work elsewhere—in regional databases and grey literature—that they can't get at. Secondly, AI technology changes very quickly indeed—which means some of the things said here might already seem out-of-date by the time this piece is revised for 2025–2026. And thirdly, this study was restricted to papers written in English – thus missing work written in other languages. With rapidly changing fields such as AI, every survey taken at a particular moment will need updating again very soon.

Closing Remarks

AI is not simply adding another tool to the startup toolkit – but changing the very terms of competition. There is now compelling evidence that AI's modes of operation – better decisions; more effectively transformed business processes; improved market performance – matter very much indeed to young firms since they operate close to the intersection of scarce resources and nascent opportunities. And then again, this framework also makes another observation: some kinds of AI-entrepreneurship strategy appear to be more successful than others – specifically, those in which efficiency gains are combined with deliberate moves towards strategic repositioning and with active engagement within entrepreneurial ecosystems. Now that both generative AI, and AI-based entrepreneurship agents (Obschonka & Fisch, 2025), will soon have evolved even further – there remains work for researchers to do in mapping out what happens next.

Funding Statement

The authors extend their gratitude to the Azman Hashim International Business School (AHIBS), Universiti Teknologi Malaysia, for facilitating and supporting this research. Funding and support were provided by:

1.Madechango (Suzhou) Information Technology Co., LTD (R.K130000.7355.1U121)

2.Kunlun Medical Technology (Suzhou) Co., LTD (R.K130000.7355.1U123)

REFERENCES

1. Abaddi, S. (2026). The Tech-Savvy Entrepreneur. Emerald Publishing. https://doi.org/10.1108/978-1-83708-132-5
2. Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3
3. Alhur, M., Omar, F., Alqirem, R., & Yousuf, A. A. N. (2025). Adopting the future: How generative AI, agentic AI, and blockchain are redefining success for Dubai's emerging start-ups. Human Behavior and Emerging Technologies, 2025, 9751686. https://doi.org/10.1155/hbe2/9751686
4. AlNuaimi, B. K., Singh, S. K., Ren, S., Budhwar, P., & Vorobyev, D. (2022). Mastering digital transformation: The nexus between leadership, agility, and digital strategy. Journal of Business Research, 145, 636–648. https://doi.org/10.1016/j.jbusres.2022.03.038
5. Balcerzak, A. P., Skapa, S., & Zinecker, M. (2025). Start-ups and artificial intelligence: From application to value, and the five problems that shape effective implementation. Oeconomia Copernicana, 16(2), 1–28. https://doi.org/10.24136/oc.4057
6. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120.
7. Belitski, M., Guenther, C., Kritikos, A. S., & Thurik, R. (2021). Economic effects of the COVID-19 pandemic on entrepreneurship and small businesses. Small Business Economics, 58(2), 593–609. https://doi.org/10.1007/s11187-021-00544-y
8. Cruz-Sanchez, O. M., Cruz-Cazares, C., & Hernandez-Vivanco, A. (2025). Business model innovation from dynamic capabilities perspective: A systematic literature review. Journal of Business Research, 190, 115835. https://doi.org/10.1016/j.jbusres.2025.115835
9. Dabrowska, J., Almpanopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., & Ritala, P. (2022). Digital transformation, for better or worse: A critical multi-level research agenda. R&D Management, 52(5), 930–954. https://doi.org/10.1111/radm.12531
10. Delgado-Sanchez, E., Calderon, R., & Herrera, F. (2025). Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. Applied Sciences, 15(12), 6465. https://doi.org/10.3390/app15126465
11. Diaz-Rodriguez, N., Del Ser, J., Coeckelbergh, M., Lopez de Prado, M., Herrera-Viedma, E., & Herrera, F. (2023). Connecting the dots in trustworthy artificial intelligence: From AI principles, ethics, and key requirements to responsible AI systems and regulation. Information Fusion, 99, 101896. https://doi.org/10.1016/j.inffus.2023.101896
12. Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. International Journal of Information Management, 59, 102168. https://doi.org/10.1016/j.ijinfomgt.2020.102168
13. Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. Information Systems Frontiers, 24(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w
14. Fossen, F. M., McLemore, T., & Sorgner, A. (2024). Artificial intelligence and entrepreneurship. IZA Discussion Paper(No. 3772). https://doi.org/10.2139/ssrn.4863772
15. Gama, F., & Magistretti, S. (2023). Artificial intelligence in innovation management: A review of innovation capabilities and a taxonomy of AI applications. Journal of Product Innovation Management, 41(1), 112–137. https://doi.org/10.1111/jpim.12698
16. Giuggioli, G., & Pellegrini, M. M. (2022). Artificial intelligence as an enabler for entrepreneurs: A systematic literature review and an agenda for future research. International Journal of Entrepreneurial Behavior & Research, 29(4), 816–837. https://doi.org/10.1108/IJEBR-05-2021-0426
17. Hagendorff, T. (2020). The ethics of AI ethics: An evaluation of guidelines. Minds and Machines, 30(1), 99–120. https://doi.org/10.1007/s11023-020-09517-8

18. Kahveci, E. (2025). Digital transformation in SMEs: Enablers, interconnections, and a framework for sustainable competitive advantage. Administrative Sciences, 15(3), 107. https://doi.org/10.3390/admsci15030107
19. Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2023). The GenAI is out of the bottle: Generative artificial intelligence from a business model innovation perspective. Review of Managerial Science, 18, 1189–1220. https://doi.org/10.1007/s11846-023-00696-z
20. Kitchenham, B. (2004). Procedures for performing systematic reviews (Report No. TR/SE/0401). Keele University.
21. Kumar, A., Shankar, A., Hollebeek, L. D., Behl, A., & Lim, W. M. (2025). Generative artificial intelligence (GenAI) revolution: A deep dive into GenAI adoption. Journal of Business Research, 189, 115160. https://doi.org/10.1016/j.jbusres.2024.115160
22. Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. Journal of Open Innovation: Technology, Market, and Complexity, 5(3), 44. https://doi.org/10.3390/joitmc5030044
23. Malik, F. S., & Terzidis, O. (2026). The metamorphosis of organizational resilience: A strategic roadmap for SMEs in the digital age. Review of Managerial Science, 20, 1–36. https://doi.org/10.1007/s11846-026-01002-3
24. Obschonka, M., & Audretsch, D. B. (2019). Artificial intelligence and big data in entrepreneurship: A new era has begun. Small Business Economics, 55(3), 529–539. https://doi.org/10.1007/s11187-019-00202-4
25. Obschonka, M., & Fisch, C. (2025). From humans to machines: Researching entrepreneurial AI agents built on large language models. Journal of Business Venturing Insights, 23, e00581. https://doi.org/10.1016/j.jbvi.2025.e00581
26. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372, n71. https://doi.org/10.1136/bmj.n71
27. Ries, E. (2011). The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses. Crown Business.
28. Soomro, R. B., Al-Rahmi, W. M., Dahri, N. A., Almuqren, L., & Almogren, A. S. (2025). A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. Scientific Reports, 15, 86464. https://doi.org/10.1038/s41598-025-86464-3
29. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.
30. Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8(1), 45. https://doi.org/10.1186/1471-2288-8-45
31. Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022
32. Wang, S., & Zhang, H. (2025). Digital transformation and innovation performance in small- and medium-sized enterprises: A systems perspective. Systems, 13(1), 43. https://doi.org/10.3390/systems13010043
33. Weng, Y. G., Salim, F. A. A., Hashim, H. I. C., Setiawan, B., & Ramli, M. F. (2025). Empowering women entrepreneurs with artificial intelligence (AI) for social sustainability: Systematic literature review. Malaysian Journal of Consumer and Family Economics, 35, 1–27. https://doi.org/10.60016/majcafe.v35.01