

# Artificial Intelligence in Startup Investment Decision-Making

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**Abstract:** Artificial intelligence (AI) is currently exhibiting rapid changes in shaping and enhancing the entrepreneurial landscape, including the startup ecosystem. While prior research has addressed innovative financial startup systems such as AI-based credit scoring and AI for financial fraud detection, the current understanding of AI's optimal role in startup evaluation remains fragmented. This study addresses the need to critically assess how AI is actually reshaping a part of the startup ecosystem, namely startup investors such as angel investors, venture-capitalists, corporate venture capital, governments, financial advisors, and private equities. This systematic literature review with bibliometric analysis examines the landscape of AI applications in startup investment decision-making across articles published over the past decade in Scopus-indexed journals. Using PRISMA systematic literature review protocols and VOSviewer, 623 articles were considered, and 67 were fully reviewed that were related to artificial intelligence, investment, and startups. We identify three phases in the implementation of AI in this area: methodological sophistication, relational learning, and generative AI. Our review also revealed several research gaps pertaining to its application or usage in several different levels of the startup investment stage. This study offers practical guidelines for practitioners and a theoretical foundation for subsequent research on AI. This research contributes to the entrepreneurship, technology management, and financial management literature by mapping evidence and identifying promising research directions for developing AI frameworks within the startup ecosystem. This study also implies that while investors should attempt AI-driven instruments for decision-making, final human calibration and evaluation should still be done to provide sound alignment with startup investors' financial or investment decisions. As such, the findings provide emphasis on responsible AI adoption within the startup ecosystem.

**Keywords:** Artificial Intelligence, Entrepreneurship, Investment Decision, Startup Valuation, Venture Capital

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## 1. Introduction

The development of the Industrial Revolution 4.0, which refers to the current trend of automation and data exchange in manufacturing technologies, has positioned startups as new drivers of innovation and economic growth (OECD, 2024). Appropriate investment in potential startups can not only facilitate technological independence and the creation of engineering talents but is also strategic in supporting government objectives, including job creation, increased productivity, innovation, and exports (Mulyawan, Aldianto and Dhewanto, 2023; Wei et al, 2025). However, experts have long described financing these types of new ventures as risky. In fact, according to the Startup Genome Project (2021), 90% of global startups fail within the first 3 to 5 years and one of the main determinants of startup failure is the lack of adequate financial resources from investors, which would enable startup founders to pursue entrepreneurial endeavours (Martielli et al, 2024). These results were obtained from 111 post-mortem analyses of startups. Therefore, understanding the factors that determine investor valuation of a company is a priority for startup development (Nursaadah & Faturohman, 2022).

The startup investment process itself is often faced with high complexity, such as high market uncertainty, information asymmetry, and reliance on subjective assessments of the founding team and untested business models (Azka & Faturohman, 2020; Beyhan et al, 2024; Topaler & Khan, 2025). Moreover, traditional investment decisions frequently depend on investors' intuition, which can lead to missed opportunities or heightened failure risk (Colombo, 2021). To address this issue, alternatives are needed to improve assessment accuracy.

An emerging technology that can potentially leverage decision-making pertaining to startup investment or financing is artificial intelligence (AI). In fact, Ferrati and Muffatto (2021) show that more and more investment companies, including Kleiner Perkins, EQT Ventures, Correlation Ventures, and SignalFire, are using data-driven methods that combine algorithms with human judgement. However, while venture capital (VC) companies are using AI more and more, little research exists to undermine these phenomena (Xu et al 2023).

The focus of this study is to provide a systematic literature review on how AI can be used to help make choices on startup investments and funding. As such, the study is organised around four research questions, which are:

**RQ1:** How has AI transformed startup investment decision-making?

**RQ2:** What investment criteria are identified as most critical across the empirical literature, and how do they vary across startup life-cycle stages?

**RQ3:** At which stages of the investment process does AI intervention offer the greatest marginal benefit?

By addressing these enquiries, this study aims to bridge the gap between theoretical understandings of artificial intelligence and practical, real-world deployment in venture capitals and other stakeholders. We contribute to the discourse on artificial intelligence by synthesising fragmented empirical findings on AI deployment in startup investment decision-making. Ultimately, this work hopes to provide insights for both practitioners seeking to optimise their investment decisions and scholars in the fields of business and management and artificial intelligence.

## 2. Methodology

### 2.1 Review Approach

The systematic literature review (SLR) approach is used in this study because it can “ensure transparency, replicability, and methodological rigour in synthesising the research body” (Pandey and Mohan, 2024). We followed the PRISMA 2020 protocol (Page et al, 2021) for SLR with four distinct stages, as shown in Figure 1, and used VOSViewer to identify relations within the network of papers.

#### 2.1.1 Identification

The search was conducted using the Scopus and Springer databases. The terms ‘startup’, ‘investment’, ‘financing’, and ‘artificial intelligence’ were combined to create a search approach that was intended to find records related to the research scope and research questions. The final search string is as below:

("invest" OR "investor" OR "investment" OR "venture capital" OR "fund\*" OR "valuation") AND ("artificial intelligence" OR "AI" OR "Predictive Analytics" OR "Natural Language Processing" OR "Large Language Models") AND ("startup\*" OR "start-up" OR "start up")

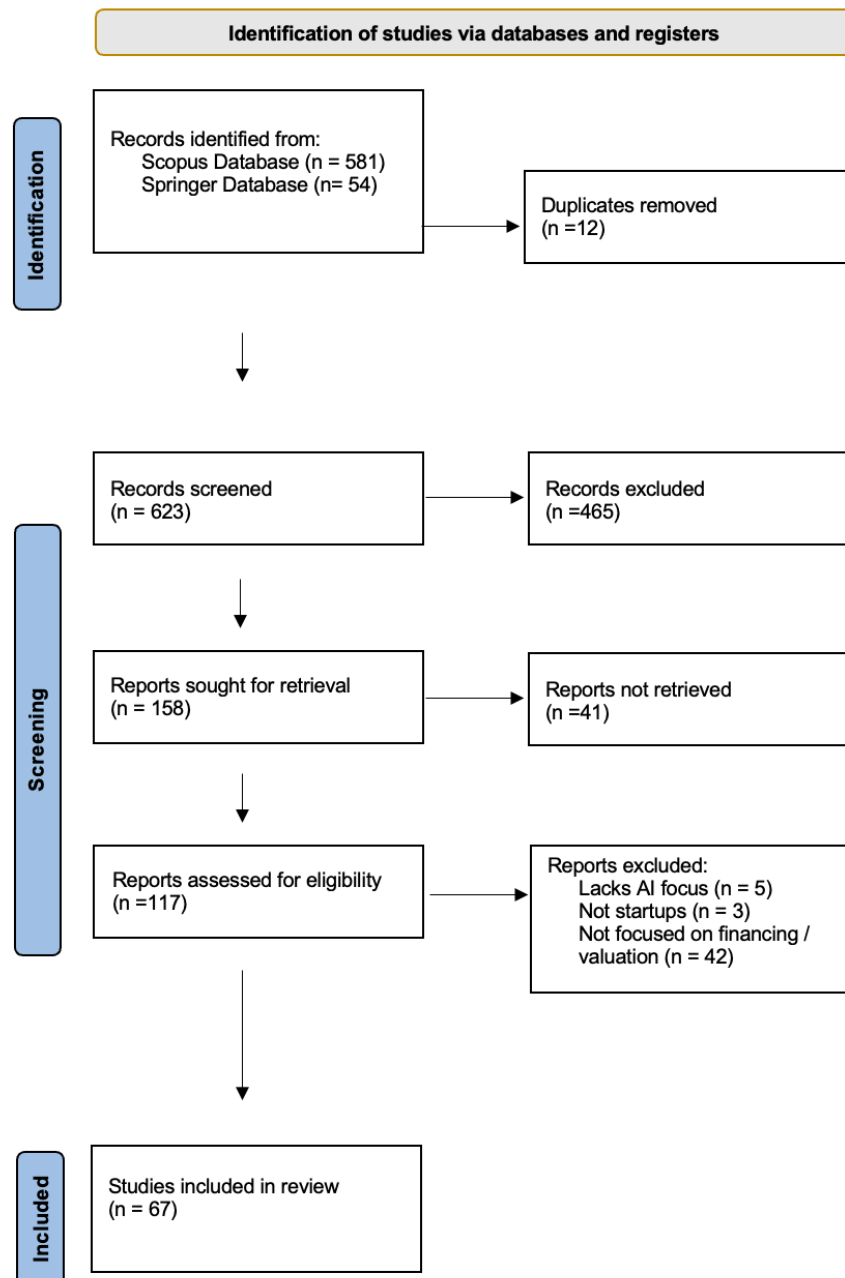
Table 1 shows the number of articles that were reduced using several inclusion criteria such as years, publication type, language, and filtered keywords. The final number of papers that were identified from both databases was 623 papers.

**Table 1: Search Results Criteria in Databases**

| Inclusion Criteria                                                         | Scopus Database | Springer Database |
|----------------------------------------------------------------------------|-----------------|-------------------|
| Search Fields: title, abstract, and keywords                               | 17,959          | 16,463            |
| Years: 2021-2026                                                           | 14,738          | 10,759            |
| Publication Type: Journal Article                                          | 10,099          | 2,071             |
| Language: English                                                          | 9,896           | 2,066             |
| Field: Business, management, accounting; economics, econometrics, finance. | 4,141           | 797               |
| Filtered Keywords: artificial intelligence, startup                        | 581             | 54                |

#### 2.1.2 Screening

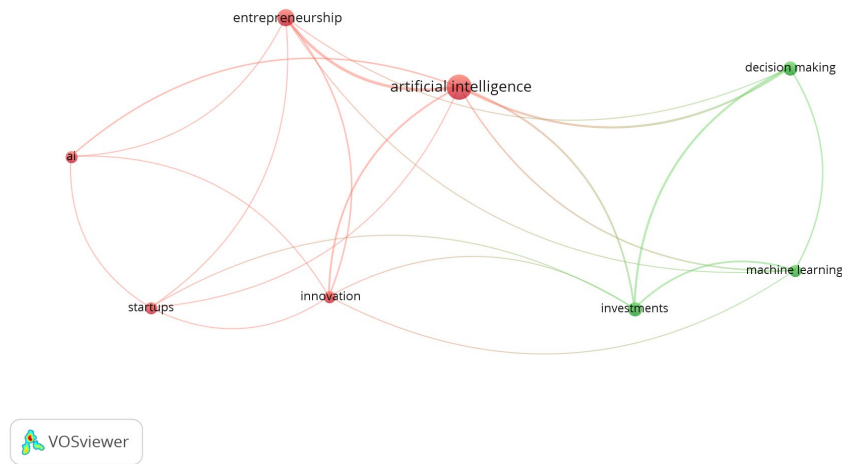
Each unique source was then assessed against pre-specified inclusion and exclusion criteria. Articles were included if they explicitly investigated the use of AI, ML, LLMs or related techniques in connection with startup or entrepreneurial-firm investment, financing, valuation, screening, recommendation or success prediction. Meanwhile, articles were excluded if they addressed AI in entrepreneurship without any link to investment or financing, covered general financing without a startup focus, or addressed startup financing or investment but without AI. The final number of studies included in this SLR is 67.



**Figure 1: PRISMA results**

### 3. Bibliometric Results

After results of articles were pooled, a bibliometric analysis was generated. First, through VOSviewer, a keyword co-occurrence network was generated to map the intellectual structure of the reviewed literature. As can be seen in Figure 2, the visualisation reveals two distinct but highly interconnected thematic clusters. The first cluster (red) encapsulates the broader startup ecosystem, characterised by strong linkages between "artificial intelligence" (the most prominent node), "entrepreneurship", "startups", and "innovation". The second cluster (green) delineates the specific operational mechanics of venture funding, highlighting the triad of "investments", "decision-making", and "machine learning". The central positioning of the artificial intelligence node illustrates its role as a pivotal bridge, demonstrating how broad entrepreneurial innovations are increasingly underpinned by specific, data-driven methodologies (such as machine learning) used to optimise investment decision-making processes.



**Figure 2: Co-occurrence results**

Next, after reviewing metadata from the included studies, we were able to track the most outlets used for publishing research relevant to this field and topic. Table 2 has identified journals with the most citations. The relatively modest citation metrics observed across these publications largely reflect the nascent and highly specialised niche of artificial intelligence applications in startup financing. Because the integration of algorithmic decision-making into venture capital is a rapidly emerging frontier, the academic discourse remains in its developmental infancy and has not yet had the longitudinal runway required to accumulate the massive citation volumes typical of more mature management disciplines.

**Table 2: Top Journals Based on Citations**

| Source                                                          | Citations |
|-----------------------------------------------------------------|-----------|
| International Journal of Entrepreneurial Behaviour and Research | 67        |
| Foundations and Trends in Entrepreneurship                      | 33        |
| Journal of Innovation and Knowledge                             | 10        |
| Journal of Technology Transfer                                  | 7         |

Finally, several respectable publications with the most citations were also discovered, as can be shown in Table 3. An examination of these works indicates that artificial intelligence is radically altering entrepreneurship across numerous levels of analysis, from macro-environmental policy to micro-level venture operations. At the ecosystem level, Hannigan (2022) demonstrates that AI, coupled with advanced text analytics like topic modelling, can uniquely capture both the cultural and material infrastructures of emerging entrepreneurial networks, thereby equipping policymakers with richer data for economic intervention. Within the corporation, AI's disruption is most pronounced in strategic decision-making (SDM). Csaszar (2024) gives solid evidence that existing big language models can analyse and produce corporate plans at a skill level comparable to seasoned investors and entrepreneurs. This cognitive augmentation extends directly into the venture conception and product development phases. Schiavone (2023) illustrates through multiple case studies how AI interventions forge new organisational processes and reduce resource costs during venture creation, while Raneri (2023) successfully operationalises this by embedding AI predictive algorithms directly into the Lean startup "build-measure-learn" loop to forecast product desirability under high uncertainty. However, despite these deep multi-level implications, the quick explosion of interest has resulted in a highly fragmented corpus of knowledge.

**Table 3: Top cited papers**

| Year | Authors                                                               | Title                                                                                                   | Citations |
|------|-----------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------|-----------|
| 2022 | Hannigan T.R.; Briggs A.R.; Valadao R.; Seidel M.-D.L.; Jennings P.D. | A new tool for policymakers: Mapping cultural possibilities in an emerging AI entrepreneurial ecosystem | 67        |
| 2024 | Csaszar F.A.; Ketkar H.; Kim H.                                       | Artificial Intelligence and Strategic Decision-Making: Evidence from Entrepreneurs and Investors        | 52        |

| Year | Authors                                                                 | Title                                                                                 | Citations |
|------|-------------------------------------------------------------------------|---------------------------------------------------------------------------------------|-----------|
| 2023 | Schiavone F.; Pietronudo M.C.; Sabetta A.; Bernhard F.                  | Designing AI implications in the venture creation process                             | 35        |
| 2023 | Raneri S.; Lecron F.; Hermans J.; Fouss F.                              | Predictions through Lean startup? Harnessing AI-based predictions under uncertainty   | 32        |
| 2026 | Uriarte S.; Baier-Fuentes H.; Espinoza-Benavides J.; Inzunza-Mendoza W. | Artificial intelligence technologies and entrepreneurship: a hybrid literature review | 32        |

## 4. Thematic Analysis and Discussion

### 4.1 RQ1: How has AI Transformed Startup Investment Decision-Making?

Several researchers have recorded the transformation of startup investment, from human-based decision-making to integrating algorithmic insight, but none have recorded the whole replacement of the human agent in decision-making. For example, Ferrati and Muffatto (2021) recorded the early shift and found seven common research goals that machine learning works on: predicting a company's exit event, predicting future funding events, predicting the next milestones, predicting investor–company relationships, making investment recommendations, predicting valuations, and classifying firms by industry. They show that random forest has generally been the most consistently effective algorithm for classification problems, with three studies achieving accuracy, recall and AUCs above 90% on the exit-prediction task. Crucially, they frame ML (machine learning) as a decision-support layer; the final commitment of capital should remain with the practitioner because predictions are not decisions.

In all, we found that AI transformation has happened in three phases. The first phase is methodological sophistication. Zhang et al (2023) develop an integrated differential-evolution and adaptive-moment-estimation neural network (Adam-ENN) tailored to early-stage valuation, outperforming least squares, ridge regression, deep neural networks and random forest on both  $R^2$  and root-mean-squared error. Blanquet et al (2025) benchmark eight algorithms (decision trees, random forest, XGBoost, support vector machines, neural networks, ridge regression, k-nearest neighbours and C5.0) and report a Mean Absolute Percentage Error of roughly 34.9%, a thirty per cent improvement over industry benchmarks. They explicitly reject deep learning for the small-sample, high-dimensional VC context and prefer Local Interpretable Model-agnostic Explanations (LIME) to SHapley Additive exPlanations (SHAP) because deal-by-deal evaluation aligns with localised explanations.

The second phase is relational learning. Xu et al (2023) develop a venture-capital knowledge graph from CrunchBase and OriginsInfo, capturing 107,507 entities and over 376,000 relations among VCs, startups, founders, employees, educational institutions, ethnic origins, cities and industries. Combining graph embeddings (using TransD) with meta-path counts, their SocioLink framework significantly outperforms four state-of-the-art benchmarks. Relational learning thus introduces a fundamentally new modality of information – the social and structural ties of investors and founders – that transactional models cannot capture.

The third phase is generative AI, which refers to artificial intelligence systems that can create content, such as text, images, or music, based on input data. For instance, Csaszar et al (2024) show that LLM scores of 138 startup-competition business plans correlate at 0.52 with the average of 250 professional investors, with intraclass reliability between LLM and VC ratings (0.51) actually exceeding inter-rater reliability among individual VCs (0.25). Ramoglou et al (2026) also argued, drawing on a Wittgensteinian language-centred view, that mastery of relevant 'language games' may itself constitute the kind of competence required for entrepreneurial narrative work. Together these papers suggest that AI now contributes not only predictive analytics but also evaluative judgement – albeit imperfect, biased and bounded judgement, as discussed under RQ4.

Apart from the deal-screening room, AI has also changed the way institutions finance deals. Antoniuk and Ivens (2026), interviewing twenty-three professionals across eighteen German entrepreneurship infrastructure organisations (EIOs), find that generative AI is automating document creation, customer queries and market analytics, while shifting expert roles toward higher-value strategic-consulting tasks. Trawnih et al (2025) demonstrate that AI, together with firm capabilities, explains 57.2% of the variance in supply chain finance outcomes for 349 Jordanian startups, with blockchain and trust playing partial mediation and moderation roles, respectively. The transformation is therefore both vertical (within investor workflows) and horizontal (across the institutions that channel capital to startups).

## 4.2 RQ2: Investment Criteria Across Life-Cycle Stages

Across the literature, investment criteria converge on five groups: team and human capital; founder and investor networks (social capital); technology and intellectual property; financial and operational signals; and market and traction signals. Their relative weight varies systematically across life-cycle stages.

### 4.2.1 Team and Human Capital

Almost every empirical paper in our sample assigns team a leading role. The ten-dimension rubric of Csaszar et al (2024) places the team at the top of the list, alongside the execution plan, financials, writing quality, innovation, market opportunity, competitive advantage, product, investment potential and viability. Carrera et al (2025) treat team characteristics as one of five Quality 4.0-aligned criteria. In their case study, the most important criterion is innovation and technology (weight 0.33), followed by team (0.22) illustrating that the weighting of team relative to technology depends on context but rarely vanishes.

### 4.2.2 Networks and Social Capital

Zhang et al (2023) report that the single most important predictor of early-stage valuation is the number of VC investors in the funding syndicate, with VC investors' social capital playing a substantial secondary role. Xu et al (2023) find that the most informative SocioLink meta-paths are employment-affiliation overlap between VC and startup employees, ethnic connection and the industry relatedness of the VC's prior investees. Networks therefore matter both directly (more co-investors signal quality) and indirectly (proximity drives matching).

### 4.2.3 Technology, IP and Innovation

Blanquet et al (2025) identify the Total Cost of Ownership and the Value Added Intellectual Capital coefficient as particularly informative for early-stage technology firms. However, Zhang et al (2023) report a striking counter-finding: patent counts convey little useful signal in early-stage entrepreneurial-firm valuation, contradicting a long tradition that treats patents as quality proxies. Carrera et al (2025), by contrast, weight 'patents and market potential' jointly at 0.20. The literature thus disagrees on the marginal value of formal IP, with the disagreement plausibly explained by sectoral and stage differences.

### 4.2.4 Financial and Operational Signals

Blanquet et al (2025) report that 37 of 54 statistically significant predictors are financial metrics, contributing the largest cumulative variance-importance score and validating the centrality of financial performance to valuation. However, they also stress that non-financial categories particularly team and management show statistically significant influence, supporting a hybrid valuation strategy that integrates traditional financial data with intellectual-capital and cost-structure indicators.

### 4.2.5 Market and Traction Signals

Siddik (2026) demonstrates that funding-stage signals themselves operate as quality cues. Analysing 561 generative-AI startups with two-stage least squares and method-of-moments quantile regression, the study shows that angel and seed funding are essential for early formation but are associated with lower total funding amounts, whereas Series A, B and C investments significantly increase total funding. Team size, investor diversity and LinkedIn engagement all amplify funding success implying that signals visible to AI scrapers are themselves valuation-relevant features.

Life-cycle stage also can shift the weights. At pre-seed and seed, with little financial history, signals about team, network and digital footprint dominate (Zhang et al 2023; Xu et al 2023). At Series A, technological proof and intellectual capital metrics like the Value Added Intellectual Capital coefficient gain weight (Blanquet et al 2025). At Series B and beyond, financial performance metrics dominate and traction signals such as prior funding stage become dispositive (Siddik 2026). The empirical message is that no single criterion is universally critical what matters most depends on where the firm sits on its development trajectory.

## 4.3 RQ3: Stages of Greatest Benefit From AI

The investment process can usefully be broken down into deal sourcing, screening, due diligence, valuation, deal structuring, post-investment monitoring and exit decisions. The literature suggests that AI's marginal benefit is largest at the upstream stages and reduces as the decision moves toward final commitment.

#### 4.3.1 Deal Sourcing and Screening

This is where the evidence is strongest. Ferrati and Muffatto (2021) note that filtering large funnels of opportunities is precisely where ML models excel, citing several studies achieving over 90% accuracy on exit prediction. SocioLink (Xu et al 2023) delivers measurable uplift over four state-of-the-art benchmarks for matching VCs with startups, with relational features explaining most of the gain. Csaszar et al (2024) demonstrate that LLMs can score business plans rapidly and consistently, with strong correlation to professional investor scores making them a natural triage layer when an accelerator faces hundreds of applications it cannot fully review by hand.

#### 4.3.2 Due Diligence and Valuation

Zhang et al (2023) show that ML can produce comprehensive valuations for early-stage firms that traditional methods cannot value at all, but emphasise the importance of partial-dependence analysis to surface non-linear relationships. Blanquet et al (2025) report a thirty-percent reduction in valuation error but explicitly require LIME-based local explanations because deal-by-deal scrutiny is the norm. Trawnih et al (2025) demonstrate that AI improves credit evaluation in supply chain finance contexts, particularly for startups underserved by traditional banks suggesting that AI's due-diligence value is highest where conventional data infrastructure is thinnest.

#### 4.3.3 Pitch Evaluation and Pitch Refinement

Two findings deserve emphasis. First, AI evaluations of pitches correlate with realised fundraising outcomes more tightly than evaluations from a benchmark sample of human investors (Kleinert and Urbig 2026). Second, AI-rewritten pitches are themselves rated higher by human evaluators by 0.14 standard deviations on average and the uplift is largest for plans previously rejected by accelerators (Csaszar et al 2024). This suggests a striking dual benefit: AI helps investors triage pitches and helps founders craft them, with potentially democratising effects for entrepreneurs without privileged networks (Ramoglou et al 2026).

#### 4.3.4 Final Commitment Under Uncertainty

This is where AI's marginal benefit narrows. Kleinert and Urbig (2026) warn that LLMs may struggle in genuinely novel situations where future possibilities are neither analysable nor predictable using statistical reasoning. Their finding that LLM survival predictions collapse for unseen ventures is a powerful caution. Sycophancy, anchoring and herding biases compound the problem. Carrera et al (2025) note that even sophisticated LCJ-based methodologies require tempering with expert judgement when comparing very heterogeneous startups. Ferrati and Muffatto (2021) echo the foundational point: predictions are not decisions, and the final go/no-go remains a human responsibility.

#### 4.3.5 Post-Investment Monitoring and Exit

Recent research does not touch much on this stage, but Ferrati and Muffatto (2021) and Blanquet et al (2025) both flag continuous valuation and recalibration as an emerging frontier. Antoniuk and Ivens (2026) also note that stakeholders see analogous opportunities for AI-supported portfolio personalisation. Marginal benefits at this stage therefore appear real but are less established empirically than benefits upstream.

In short, AI's marginal benefit is greatest where the volume of candidates is large, the data signals are noisy but plentiful, and final stakes are not yet committed. Aziz et al (2026) synthesizes the implication: AI amplifies entrepreneurs' and investors' intellectual capital, but its responsible use requires explicit ethical frameworks addressing bias, transparency and data privacy, especially in resource-constrained contexts.

## 5. Conclusion

This review on the use artificial intelligence in startup investment or financing finds a research field in its early years. Through rigorous SLR methods, we found that (RQ1) classical machine learning and generative AI have changed how startup funding decisions are made by adding predictive, relational, and evaluative layers to a process that used to be dominated by intuition. Nevertheless, at the point of commitment, human judgement is still used. When it comes to investing, the most important factors (RQ2) are team and human capital, networks and social capital, technology and intellectual property (IP), financial signals and market signals. The importance of these factors changes regularly between the seed, Series A, and later stages of a business's life. AI evaluations

and investor tastes are not the same. The marginal benefit (RQ3) is strongest during deal sourcing, screening, and pitch evaluation. It is moderate during due diligence and valuation, and it is lowest during final commitment when there is real uncertainty

Several implications are apparent. First, for investors, AI is best viewed as a sophisticated decision-support layer rather than a replacement for human judgement; the most rigorous studies in the bulk of literature consistently report augmentation rather than substitution. Second, for entrepreneurs, the same tools that empower investors also empower founders. LLMs can polish pitches, simulate investor feedback and democratise access to high-quality strategic advice (Csaszar et al 2024; Ramoglou et al 2026). Third, for policymakers and infrastructure providers, opportunities include extending financing access through AI-blockchain supply chain finance (Trawnih et al 2025) and AI-augmented EIOs (Antoniuk and Ivens 2026); obligations include enforcing transparency, auditing for bias and protecting data privacy (Aziz et al 2026).

The bulk of literature also shows clear gaps. Most ML works use Crunchbase or single-region samples, leaving generalisability open. LLM evaluations have been tested primarily on equity-crowdfunding pitches and accelerator competitions rather than professional VC pipelines. Interpretability methods are improving but rarely linked back to investor decision-quality results. Ethical frameworks stay largely aspirational. Finally, the field has yet to grapple seriously with the systemic and reflexive effects of mass AI adoption: if every VC uses similar models learned on similar data, will deal flow homogenise, valuations correlate and tail risks concentrate? These questions point to a rich agenda for further work bridging entrepreneurial finance, AI methodology and the political economy of invention. In sum, AI is reshaping startup investment and financing choices, but the most robust evidence in the literature argues for a hybrid future in which algorithmic insight is married to, not divorced from, human knowledge.

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## Ethics Declaration

This research is a desk-based systematic literature review that uses only published, peer-reviewed scholarly works. No human or animal participants were involved, and no primary data were collected. Ethical clearance was therefore not required.

## AI Declaration

Generative AI tools were used to assist with literature scanning, paraphrase generation and formatting during the drafting of this paper. All claims are grounded in the cited sources, all citations were verified by the authors against the original documents, and the authors take full responsibility for the content, interpretation and conclusions presented in the paper.

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