Artificial Intelligence in Startup Investing: Opportunities, Challenges, and Human-AI Collaboration

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Abstract. This paper presents a study on the integration of Artificial Intelligence (AI) in Venture Capital (VC) decision-making. Drawing on recent academic and applied research, the study aims to investigate the key domains where AI is deployed in VC processes and the evolving relationship between human investors and AI tools. The review highlights that AI is increasingly used in deal sourcing, startup screening, due diligence, valuation modelling, and exit prediction. While AI demonstrates advantages in speed, scalability, and objectivity—particularly in pattern recognition and bias reduction—it also presents notable limitations. These include dependency on historical data, difficulty in assessing qualitative founder traits, and risks of perpetuating algorithmic biases. Consequently, a hybrid approach is advocated, where AI augments but does not replace human expertise. Moreover, the study examines how AI is changing investor behaviour and the nature of investor–founder relationships. AI is generally used to augment rather than replace human judgment, supporting decision-making rather than automating it. This shift raises new considerations around trust, transparency, and fairness in human–AI collaboration. The research concludes that while AI holds transformative potential for venture capital—enhancing efficiency, objectivity, and scalability—a hybrid approach that combines algorithmic insights with human expertise remains essential. Ethical adoption, attention to qualitative factors, and the design of explainable and inclusive AI systems will be critical to maximizing its benefits in startup investment.

Keywords: Artificial intelligence, Venture capital, Startup risk assessment, Decision support systems, Entrepreneurship, Human–AI collaboration

1. Introduction

Venture capital (VC) serves as a critical engine for innovation, providing early-stage funding to high-risk, high-potential startups in rapidly evolving sectors such as technology, life sciences, and clean energy. Traditionally, VC decision-making has relied heavily on human intuition, personal networks, and qualitative judgment (Gompers P. K., 2020) . However, as the scale and complexity of startup ecosystems grow, these methods face increasing limitations. In this context, artificial intelligence (AI) has emerged as a promising tool to enhance the speed, efficiency, and objectivity of venture investment processes ((Röhm, 2022), (Di Giannantonio, 2022)).

Recent advances in AI—particularly in machine learning (ML), natural language processing (NLP), and large language models (LLMs)—are enabling VC firms to integrate algorithmic tools into key areas of their workflows. Applications include automated deal sourcing, startup screening, due diligence, valuation modeling, and exit prediction ((Bai, 2021), (Gautam, 2023)). These systems can process and analyze large volumes of structured and unstructured data, generating predictive insights that may be overlooked by human analysts.

Despite these advantages, the integration of AI into VC decision-making is not without limitations. Many models rely on historical data, which can perpetuate existing biases and fail to account for the novelty of disruptive startups (Te, 2023). Moreover, AI struggles to evaluate qualitative factors such as founder resilience, vision, and team dynamics—traits that are often decisive in entrepreneurial success (Li, 2021). These constraints underscore the necessity of a hybrid decision-making model in which AI augments rather than replaces human expertise (Zhang R., 2022).

This study investigates how artificial intelligence is transforming startup investing by conducting a systematic literature review of academic and applied research from 2020 to 2024. The review is structured around two guiding research questions:

RQ1: What are the key domains where AI is deployed in VC processes?

RQ2: How is the relationship between human investors and AI tools evolving?

To address these, four thematic areas are explored: the domains of AI application, AI-supported models for startup risk evaluation, the strengths and limitations of AI in early-stage investments, and the observed effects of AI integration on investor behavior and founder relations.

The findings reveal that AI is increasingly integrated into the VC value chain, particularly for screening and analytics tasks. Studies show that ML models such as support vector machines, random forests, and gradient boosting classifiers can achieve strong predictive performance ((Gautam, 2023), (Li, 2021)). Yet, researchers consistently advocate for a human-in-the-loop approach, where investors interpret algorithmic insights through the lens of strategic and contextual understanding ((Röhm, 2022) , (Setty, 2024)).

This paper contributes to the growing body of knowledge on governing and integrating AI in decision-making contexts, particularly in financial domains characterized by uncertainty and asymmetric information. It underscores the importance of explainability, ethical design, and trust-building in shaping the future of human–AI collaboration in entrepreneurial finance.

2. Background

Artificial intelligence is increasingly shaping the venture capital (VC) landscape, offering tools to enhance decision-making across key investment stages. This background section outlines three core areas of inquiry: the limitations of traditional VC practices (Gompers P. &., 2001), the integration of AI into deal sourcing, screening, and valuation ((Bai, 2021) , (Gautam, 2023)), and the emerging need for hybrid, human–AI collaboration models due to ethical, qualitative, and technical limitations ((Röhm, 2022), (Te, 2023)). Together, these areas frame the opportunities and governance challenges of AI in startup investing.

2.1 Venture Capital Decision-Making

Venture capital (VC) has long served as a cornerstone of entrepreneurial finance, enabling startups to develop innovative products and services while navigating uncertain and volatile market environments. The role of VC is particularly critical during the early stages of firm development, where traditional funding options are often inaccessible due to high risk, lack of collateral, or insufficient track records (Gompers P. &., 2001). In these contexts, investors must make complex decisions based on incomplete, heterogeneous, and often non-standardized information—a task that heavily relies on experience, networks, and subjective judgment (Zhang R., 2022).

However, the rise of artificial intelligence (AI) is beginning to shift this dynamic. Over the past decade, AI technologies, particularly those grounded in machine learning (ML), have shown increasing potential to augment decision-making in fields characterized by uncertainty and high data complexity—including finance, healthcare, and supply chain management (Brynjolfsson, 2017). Venture capital is now emerging as a domain where AI can offer significant operational and strategic benefits, by helping investors make more informed, data-driven decisions while reducing cognitive biases and processing inefficiencies ((Röhm, 2022), (Di Giannantonio, 2022)).

2.2 Where and How AI Is Being Used

AI in VC is typically applied in five interrelated domains: deal sourcing, startup screening, due diligence, valuation modelling, and exit prediction (Bai, 2021). In deal sourcing, AI algorithms can scan vast datasets—such as social media feeds, startup databases, and patent filings—to detect early signals of high-potential ventures (Gautam, 2023). For example, Natural Language Processing (NLP) tools are increasingly used to extract relevant insights from unstructured text data, enabling early identification of market momentum and founder expertise. In screening and evaluation, supervised learning algorithms such as logistic regression, random forests, and support vector machines (SVM) have been deployed to predict startup success based on features such as team composition, product-market fit, funding history, and competitive landscape ((Li, 2021), (Zhang R., 2022)).

Due diligence processes are also being redefined by AI integration. Traditionally time-consuming and labor-intensive, due diligence can now be accelerated using automated document extraction, sentiment analysis, and risk-scoring tools. Large language models (LLMs), in particular, are proving effective in analysing business plans, pitch decks, and legal contracts, streamlining the vetting of investment opportunities (Setty, 2024). Similarly, AI-powered valuation models have been proposed to overcome the difficulty of pricing startups that lack historical performance records or standardized financial statements. Techniques such as evolutionary algorithms, deep learning, and hybrid modelling (e.g., Adam-ENN) offer more flexible and data-sensitive approaches to startup valuation (Zhang R., 2022).

2.3 Limitations and Toward Hybrid Collaboration

Despite these technological advancements, the deployment of AI in venture capital is not without limitations. One of the most prominent challenges is data quality and availability. Many early-stage startups operate in stealth mode or lack sufficient public information, making it difficult to feed AI models with reliable, comprehensive training data. Moreover, the heavy reliance on historical data may reduce the adaptability of AI models to novel or disruptive business models that deviate from past patterns (Te, 2023).This can result in systematic underestimation of innovation potential, especially for startups led by underrepresented founders or emerging from unconventional backgrounds.

Another key limitation concerns qualitative evaluation, particularly in assessing intangible founder traits such as resilience, leadership, adaptability, and vision. These attributes, often central to startup success, are difficult to capture using quantitative metrics alone (Li, 2021). As a result, AI tools—while valuable for filtering and standardizing inputs—must be paired with human judgment capable of contextualizing and interpreting these softer dimensions. Over-reliance on algorithmic decision-making may also risk reinforcing existing biases encoded in historical datasets, thereby entrenching inequities in venture funding (Te, 2023).

These challenges have prompted a growing consensus around the need for hybrid decision-making approaches in venture capital. In such models, AI serves as a decision support system, offering preliminary insights, trend analyses, and risk assessments, while human investors retain responsibility for strategic alignment, interpersonal evaluation, and final decision-making (Röhm, 2022).Several studies have emphasized the importance of transparency, explainability, and ethical governance in designing AI tools that are trustworthy and inclusive ((Setty, 2024), (Te, 2023)).

Furthermore, AI's integration is altering not only internal VC workflows but also the nature of investor–founder relationships. As more aspects of the investment process become automated, trust and communication dynamics are evolving. Founders may face pressure to "fit the model" rather than present a compelling vision, and investors must balance algorithmic recommendations with relational insight. These shifts raise new questions about accountability, transparency, and fairness, which are central to the broader discourse on AI governance in organizational and financial contexts (Brynjolfsson, 2017).

In light of these developments, it becomes increasingly important to systematically assess how artificial intelligence is currently being deployed in venture capital and what implications this holds for investment decision-making. Although individual studies have addressed specific applications—such as deal sourcing (Gautam, 2023), risk modeling (Li, 2021), or fairness in predictive analytics (Te, 2023)—there is a lack of comprehensive synthesis that connects these insights across domains. Furthermore, the evolving interplay between algorithmic tools and human judgment, often emphasized as essential for responsible decision-making ((Röhm, 2022), (Setty, 2024)),remains underexplored in an integrated framework.

3. Methodology

To systematically investigate how artificial intelligence (AI) is integrated into venture capital (VC) decision-making—particularly in the areas of startup screening, risk assessment, and investor–founder relationships—this study employs a structured literature review methodology. The goal is to synthesize academic knowledge and applied insights that address two core research questions: (1) What are the key domains where AI is deployed in VC processes? and (2) How is the relationship between human investors and AI tools evolving?

The methodology follows the well-established guidelines outlined by Kitchenham (2004) for conducting systematic literature reviews in technology-driven research fields. This approach is especially appropriate given the interdisciplinary nature of the topic, which spans artificial intelligence, entrepreneurship, finance, and organizational behavior. In order to enhance transparency and replicability, the review process is also informed by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework proposed by Moher et al. (2009). The PRISMA model is used to structure the review process, including search strategy, filtering, and documentation of inclusion and exclusion criteria.

The review was conducted using the Scopus database, chosen for its broad academic scope and high-quality indexing across both technical and business disciplines. The search query used is:

"AI" OR "Artificial Intelligence" OR "Machine Learning" AND "Venture Capital",

applied to the Article Title and Keywords fields. This search yielded a total of 5,788 results, covering a wide range of documents including journal articles, conference papers, and reviews.

To focus the review on disciplines most relevant to our research objectives, we filtered results by subject areas including Business, Management and Accounting, Economics, Econometrics and Finance and Decision Sciences. This step narrowed the dataset to 71 documents, improving thematic relevance to AI applications in VC and startup analysis.

Next, a publication date filter was applied to capture recent developments in AI research and its adoption in VC settings. Only documents published from 2020 onward were retained, reducing the corpus to 65 papers. This temporal boundary ensures the inclusion of state-of-the-art contributions, particularly those addressing the latest machine learning models and evolving investor practices.

A title and abstract screening followed, using a qualitative relevance test based on the study's research questions. Documents were excluded if they lacked accessible full texts, were not peer-reviewed, or did not directly address AI applications in VC decision-making, startup evaluation, or human–AI interaction.

After this rigorous selection process (Figure 1), 21 peer-reviewed academic papers were retained for full-text review and qualitative analysis. These articles provide the foundation for the thematic synthesis presented in the following sections, offering a multi-dimensional understanding of AI's role in venture capital decision-making, its technical capabilities, human-AI dynamics, and ethical implications.

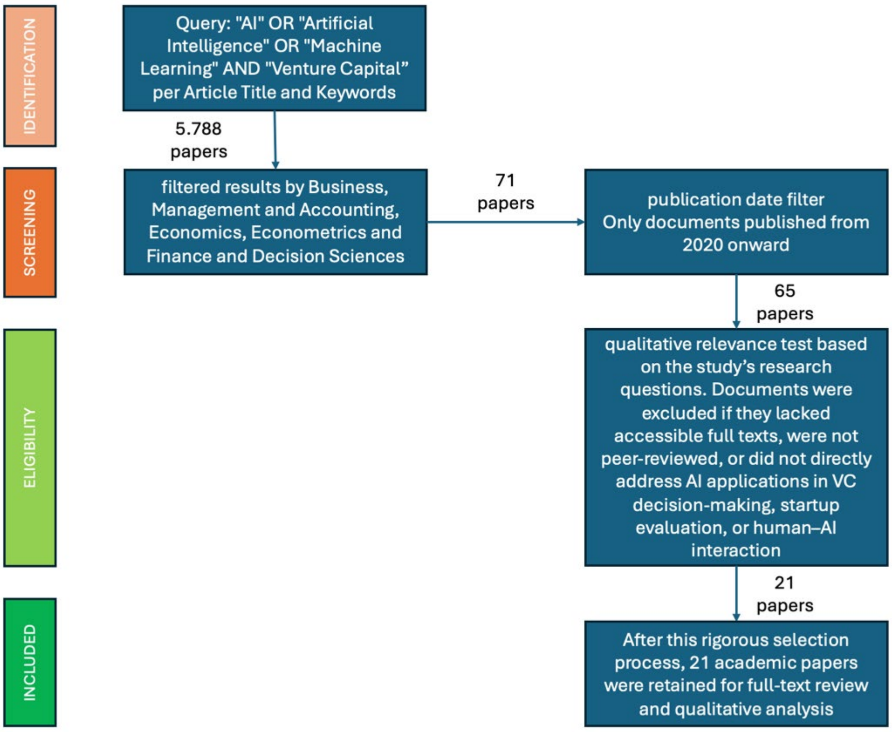

Figure 1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework

4. Discussion

The integration of artificial intelligence (AI) into venture capital (VC) decision-making marks a significant shift in how investors source, evaluate, and support startups. This discussion responds to two guiding research questions: (1) What are the key domains where AI is deployed in VC processes? and (2) How is the relationship between human investors and AI tools evolving? Drawing from 21 peer-reviewed studies published between 2020 and 2024, the analysis reveals that AI adoption in VC spans key operational domains—including deal sourcing, startup screening, due diligence, valuation, and risk prediction—while also transforming the roles, responsibilities, and judgment processes of human investors. Notably, most scholars support a hybrid model where AI augments, but does not replace, human decision-making. This section presents findings for each research question and outlines critical opportunities and limitations emerging in AI-enabled venture capital.

4.1 Key Domains Where AI Is Deployed in VC Processes

AI is increasingly applied across the VC investment cycle—from early-stage deal sourcing to late-stage valuation and exit prediction. Its most widespread applications include deal identification, startup screening, due diligence, financial modelling, and risk assessment. The automation of deal sourcing has become a central application of AI in VC. AI tools enable investors to mine massive databases and unstructured content from platforms such as Crunchbase, LinkedIn, and Twitter to identify emerging startups with promising signals ((Gautam, 2023); (Assadi, 2021)). He et al. (2021) demonstrate that ensemble models combining support vector machines and decision trees are effective in detecting fast-scaling startups by analysing founder experience, sector patterns, and investor networks. These tools improve scalability and objectivity by widening the pipeline beyond traditional human networks.

Once potential opportunities are identified, AI facilitates evaluation through predictive models trained on historical success indicators. Studies by Bai and Zhao (2021) and Gautam and Wattanapongsakorn (2023) describe machine learning–enhanced venture scorecards, where models assign probability scores based on variables such as founding team composition, product readiness, and prior investment rounds. Di Giannantonio (2022) and Setty et al. (2024) show how AI systems assist in distinguishing between viable and non-viable startups by correlating structured (e.g., team size, funding stage) and unstructured (e.g., business model narrative) data. Battistella et al. (2023) further explore clustering techniques and k-nearest neighbour algorithms to group startups by behavioural and strategic similarities, improving comparative assessments—especially useful in filtering high volumes of applications for accelerator programs or corporate venture initiatives.

The due diligence phase has also benefited from advances in natural language processing (NLP) and large language models (LLMs). Maarouf et al. (2023) show that LLMs can process founders' pitch decks, websites, and legal documents to extract key themes, risk flags, and sentiment indicators, reducing manual workload and accelerating time-to-decision. Similarly, Samudra et al. (2024) demonstrate that LLMs can standardize and analyse business plans and financial projections, offering consistency and efficiency in document evaluation.

AI is also being deployed for valuation modelling and exit prediction. Zhang et al. (2022) developed an Adam-enhanced evolutionary neural network (Adam-ENN) that outperformed traditional discounted cash flow (DCF) models in predicting valuation ranges for early-stage ventures. Das et al. (2021) introduced CapitalVX, a machine learning system that forecasts IPO, acquisition, or failure based on funding trajectory, sector dynamics, and macroeconomic indicators. Valuation is notoriously difficult at the early stage due to limited data and high uncertainty, but the combination of long short-term memory (LSTM) models (He, 2021) and generative approaches offers improved forecasting for investor decision-making. These methods help optimize portfolio allocations, anticipate exit scenarios, and balance risk exposure.

Risk prediction models are another recurring theme in the literature. Setty et al. (2024) propose a cost-sensitive model that accounts for the asymmetric costs of false positives and false negatives in VC investments. Röhm (2022) and Assadi (2021) emphasize AI's utility in flagging failure patterns such as team turnover, client concentration, or poor cash flow. However, Te et al. (2023) critique these models for embedding historical biases that disadvantage underrepresented founders or unconventional business models.

Real-time portfolio monitoring also represents an emerging application area. Battistella et al. (2023) outline predictive analytics dashboards used in post-investment phases to track changes in startup performance and enable earlier interventions.

In summary, AI tools are now deployed extensively throughout the VC process, particularly where data-driven assessments improve speed, scale, and standardization. However, their effectiveness remains constrained by data quality, model interpretability, and the inability to replicate the nuanced judgment of human investors.

4.2 Methodological and Data Patterns

Across the reviewed papers, the predominant methodological orientation is quantitative and machine-learning-based. Most studies apply supervised learning algorithms—random forests, support vector machines, gradient-boosted trees, and hybrid ensemble networks—to predict startup success, funding probability, or exit likelihood. A smaller but rapidly growing subset employs LLMs for text mining, sentiment extraction, and automated due diligence.

Data sources are largely secondary and public, including Crunchbase, PitchBook, LinkedIn, and patent databases. Some works integrate unstructured textual data from pitch decks, news articles, and financial documents. A recurring limitation concerns data incompleteness and survivorship bias—particularly in early-stage startups, where financial histories are sparse. Consequently, predictive performance declines when informational asymmetries are high or data reflect historical inequities.

Evaluation metrics commonly include accuracy, AUC, F1-score, and precision–recall balance, though few studies assess domain-specific error costs (e.g., the financial asymmetry between false positives and false negatives). This methodological gap suggests that future research should align model evaluation with the unique payoff structures of venture investing.

4.3 The Relationship Between Human Investors and AI Tools

The integration of AI into VC is not purely technical—it is reshaping investor behaviour, decision-making culture, and investor–founder interactions. A consensus emerges across the literature that AI functions best in a complementary, rather than substitutive, role. Röhm (2022), Di Giannantonio (2022), and Setty et al. (2024) consistently argue that investors employ AI for structured, data-heavy tasks but continue to rely on intuition and experience for final judgment. This hybrid model—where AI provides predictive inputs and humans contextualize them—has become a normative standard.

Gautam and Wattanapongsakorn (2023) emphasize that AI performs well in filtering and pre-screening, while humans remain superior at evaluating founder chemistry, vision, and team cohesion. Bai and Zhao (2021) caution that overreliance on AI scorecards can reproduce selection bias, with investors disproportionately favouring ventures that fit historical molds. To counteract this, Röhm (2022) recommends maintaining human override mechanisms and embedding AI outputs within broader deliberative processes.

Explainability is a decisive factor in AI adoption. Investors are more likely to trust AI outputs when they understand how predictions are generated. As Te et al. (2023) and Setty et al. (2024) note, opaque black-box models can limit uptake, especially in firms lacking internal data science capabilities. To improve interpretability, several VC firms implement SHAP values or LIME visualizations that show which variables most influence startup ratings (Maarouf, 2023). Trust also extends to investor communication with limited partners (LPs): AI-augmented decisions must be justified and auditable. This has prompted the establishment of new governance norms emphasizing transparency, model documentation, and algorithmic review boards (Di Giannantonio, 2022).

A critical issue in the human–AI relationship concerns algorithmic bias. Te et al. (2023) demonstrate that models trained on historical data reproduce structural exclusions, systematically under-scoring women- or minority-led startups. To mitigate these effects, fairness-aware machine-learning techniques and anonymized screening tools have been proposed (Setty, 2024). Röhm (2022) and Battistella et al. (2023) highlight the emergence of AI governance frameworks—internal protocols that monitor bias, validate models, and ensure accountability. Such practices signal a maturing approach in which VCs treat AI not as a black-box oracle but as a strategic, auditable decision-support tool.

Finally, AI also influences founder behaviour. LLM-based evaluation tools shape how entrepreneurs craft their pitch materials, as founders adapt content to align with algorithmic evaluation criteria. While this optimization increases efficiency, it risks diminishing authenticity and reinforcing conformity ((Maarouf, 2023); (Assadi, 2021)). The relational dimension of venture capital—historically rooted in trust and personal chemistry—must therefore integrate algorithmic assessment without losing its human core.

4.4 Practical Implications and Thematic Synthesis

Synthesizing the reviewed literature reveals that AI provides the greatest benefits in data-intensive and repetitive tasks, such as deal sourcing, information extraction, and risk monitoring, while performing less effectively in context-dependent evaluations that require social and emotional intelligence. The evidence converges on the value of hybrid human–AI decision architectures combining algorithmic scalability with human contextual judgment.

Furthermore, the literature highlights the emergence of governance practices designed to ensure accountability: explainability techniques (e.g., SHAP, LIME), fairness-aware preprocessing, model documentation, and explicit override mechanisms. These developments signal a transition from experimental tool adoption to structured, ethically guided AI management in venture capital.

Despite progress, persistent challenges remain—particularly concerning data diversity, model generalizability across markets, and the long-term behavioural impact of algorithmic systems on both investors and founders. Continued research should prioritize longitudinal validation, cross-sector replication, and comparative studies on how AI influences investment culture and equity in startup funding

5. Conclusion

This study sets out to examine the growing role of artificial intelligence (AI) in venture capital (VC) decision-making, with particular attention to two guiding questions: (1) In what domains is AI being deployed across VC processes, and (2) how is the relationship between human investors and AI tools evolving? Drawing on a systematic literature review of 21 peer-reviewed publications from 2020 to 2024, the findings provide a nuanced understanding of both the functional applications and organizational implications of AI in startup investing.

The evidence strongly suggests that AI is being integrated across nearly every stage of the VC pipeline. Machine learning models are used to enhance deal sourcing by mining platforms such as Crunchbase and LinkedIn for emerging venture signals ((Gautam, 2023), (Assadi, 2021)). Startup screening has evolved from intuition-driven judgments to data-informed processes via supervised learning models and algorithm-enhanced scorecards ((Bai, 2021), (Li, 2021)). In due diligence, natural language processing and large language models are automating the review of pitch decks, legal documents, and financials ((Maarouf, 2023), (Samudra V. C., 2024)). More advanced applications include valuation modeling using evolutionary neural networks (Zhang R., 2022) and exit prediction tools like CapitalVX (Das, 2021). These applications enable more scalable, efficient, and standardized investment workflows.

However, the findings also highlight substantial limitations that constrain the complete automation of VC judgment. Human investors remain essential due to AI's inability to evaluate intangible factors such as founder resilience, narrative coherence, or strategic vision ((Di Giannantonio, 2022), (Röhm, 2022)). Thus, a hybrid model—wherein AI augments but does not replace human decision-making—has emerged as the most widely endorsed strategy (Setty, 2024).

Ethical considerations are also central to this human–AI collaboration. AI models trained on biased data can unintentionally exclude women- and minority-led startups (Te, 2023), potentially reinforcing existing inequalities. This concern is prompting the development of fairness-aware machine learning practices and explainable AI protocols ((Setty, 2024), (Röhm, 2022)). Moreover, investors now require transparent and interpretable systems to maintain trust both within their teams and with limited partners.

Ultimately, AI holds transformative potential for venture capital by enhancing decision accuracy, reducing cognitive biases, and enabling greater scalability. Yet, these benefits are only realized when combined with strategic human oversight, model governance, and ethical alignment. As the VC industry increasingly adopts AI-driven tools, future research should investigate how these technologies perform longitudinally, particularly in capturing emerging market shifts and non-traditional innovation. The evolving investor–founder relationship and the need for adaptive organizational structures also warrant deeper exploration. Ensuring that AI augments human creativity, rather than suppresses it, will be critical to fostering a more equitable, efficient, and innovative venture ecosystem.

Ethics Declaration: This study is based on a systematic review of existing published literature. No primary data collection involving human participants, animals, or sensitive personal information was conducted. Therefore, ethical approval and clearance were not required for this research.

AI Declaration: Artificial Intelligence tools were used during the preparation of this paper to support organizational tasks, such as identifying connections and thematic matches between reviewed papers following the literature review and analysis. Additionally, AI-assisted tools were employed for grammar checking and improving language clarity after the manuscript was completed. The research design, analysis, interpretation, and final arguments remain the sole responsibility of the authors.

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