

## Venture capital and risks in growth stages of artificial intelligence tech start-ups

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### ABSTRACT

Venture capital (VC) investment is important for the growth and innovation of artificial intelligence (AI)-driven tech start-ups, which are often characterized by high uncertainty and rapid technological change. While existing literature has explored general risk factors in AI start-ups, however, limited understanding of how these risks vary across different stages of start-up development. This study addresses this gap through a systematic literature review (SLR) of 29 studies published between 2019-2024, sourced from IEEE Xplore, Web of Science (WoS), Scopus, and ProQuest databases. Guiding investment lifecycle, risks management and ISO 31000 principles, the study identified key risks variations including market, operational, financial, technological, performance, regulatory and exit risks faced by AI tech start-ups during the seed and early, growth and maturity stages. Findings indicate that early-stage start-ups are more affected by funding, market entry, and feasibility risks, while at growth stage face issues with scaling and resource management, maturity stage with regulatory and exit-related risks become more significant. A taxonomy matrix is developed to categorize these risks in a stage-specific and AI-relevant context. The review contributes to the literature by offering a structured understanding of how VC related risks evolve across start-ups stages and highlights the need for further empirical research to validate these findings and guide better investment decisions.

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## 1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed the global digital economy and created new opportunities for technology-driven entrepreneurship. According to the International Data Corporation (IDC), AI is projected to contribute \$19.9 trillion to the global economy by 2030 [1]. The potential of AI to interrupt legacy business models with significant impacts a traditional company's scalability and enhanced decision making [2] with customer experience and revenue growth, and originator and facilitator of innovation and adapt changing markets and create value [3]. This has led to a rise in AI start-ups that are characterized by a common interplay between technological breakthroughs, shifting market demands and strategic reorientations [2]. AI-driven tech start-ups are the forefront of this transformational multifaceted journey. These start-ups are often founded by technologists and innovators, leverage AI technologies not just as tools but as integral components of their business models. They tend to

create new value propositions and enhance operational efficiency [4], while connecting the power of advanced data analytics to develop customer-centric innovative solutions with AI-driven products and services [2]. These start-ups need significant funding to manage high costs associated with research and development [2], supportive technical infrastructure for AI integration [4]. Venture capital (VC) is a key enabler by providing financial support, strategic guidance, and industry networks to help in scaling up and competing globally [5]. VC is a form of equity financing that deals with funding at early stages of start-ups and new businesses [6]. According to the New York Times (2024), global VC investment in AI start-ups has surged even amid economic fluctuations. In 2024, investors invested \$27.1 billion into AI start-ups [7] reflecting growing confidence in AI-innovations. However, this investment is fraught with challenges and risks including lack of quality investment, excessive regulations, operational, and industry challenges [8]. These risks often result in financial stability and sustain start-up growth and profitability [2]. These issues frequently stem from misaligned expectations between investors and start-ups, contributing to delayed product development and difficulties in scaling. As Floridi [9] cautions, unchecked VC enthusiasm can inflate an AI ‘tech bubble’ where investment outpaces real economic value and weak regulation fails to rein in hype, underscoring why stage-aware risk taxonomy is critical to promote more effective and grounded investment decisions and start-up growth.

Despite this recognized need for a structured understanding of risk, current literature lacks a systematic analysis of how risk factors evolve across different growth stages of AI start-ups. The current literature mainly focuses on individual risk types like market or technology while providing broad insights into VC investment patterns without addressing the stage-specific and unpredictable nature of risks in AI domain. Moreover, limited synthesis exists on how start-up maturity shapes investors’ risk perceptions in AI-driven tech start-ups. This lack of structured, stage-based knowledge continues to constrain effective decision-making for both investors and founders. To address this gap, this study adopts a systematic literature review (SLR) to map and synthesize fragmented evidence and identify stage-specific risk categories. Accordingly, this research seeks to fill the identified gap and answer the following questions: i) what are the key risk variations affecting VC investment in AI driven tech start-ups? and (ii) what are the differences in these risks across the growth stages of AI driven tech start-ups and VC investments?

This review identified and categorized the key risks influencing VC investments in AI-driven tech start-ups across different growth stages. By offering a stage-specific risk taxonomy, the study supports VCs in aligning due diligence processes and investment strategies more effectively. It also offers insights for AI start-ups founders to better understand investor concerns at each growth stage and prepare stronger funding approaches. Academically, the review addresses a critical gap by exploring how investment risks vary across stages and provides a foundation for future empirical research to support informed investment decisions.

## **2. THEORETICAL BASIS**

### **2.1. AI driven tech start-ups**

AI-driven tech start-ups lack a universally accepted definition in entrepreneurship and innovation literature, uses overlapping terms for ventures applying AI in varying capacities. Drawing on previous studies, these start-ups are taken as new entrepreneurial firms or start-ups, scaled rapidly by embedding AI as a core value-creation mechanism rather than a supporting tool. These start-ups leverage machine learning (ML), natural language processing (NLP), and related AI technologies to enhance decision-making, automate processes, and deliver personalized offerings [10], while gaining efficiency, accuracy, and competitive advantage [11]. Such start-ups experiment with emerging AI technologies such as deep learning and computer vision to develop adaptive and evolving solutions [2] and pursue commercialization of AI-centric innovations in areas including deep learning, visual recognition, computer vision, or from innovative recombination of existing AI methods [3]. These require considerable resources to build AI capabilities through AI factory approach while optimizing scale, scope, and learning through the management of AI processes [12], as shown in Figure 1. These AI start-ups rely on VC investment to establish AI factories and manage AI-related processes and risks [12]. This foundational understanding provides a basis examining the role of VC in supporting their development and long-term growth efficiency, particularly the unique risk realities associated with data, model training, and talent intensity.

### **2.2. VC investment in AI driven tech start-ups**

Recent studies suggest that VCs play a critical role in supporting AI-driven tech start-ups by enabling the development of AI factories [12] that centralize data processing [13], model training [14], and deployment processes thereby reducing the data risks [12], and supporting scalability. Beyond capital, VCs provide business and financial support [12], which accelerates growth of AI start-ups but also introduces specific risks requiring careful evaluation. However, VC investment in AI remains lacking from an operational perspective [15]. Prior studies emphasized funding and strategy with limited attention to AI

specific monitoring, due diligence, and technical assessment differ when investing in AI start-ups compared to conventional tech ventures. Therefore, AI start-ups represent a new driver of value proposition through AI capabilities, provide different roles of data for value creation and the offering an impact of technology on overall business logic, while elaborating promising directions for entrepreneurship and significant economic impact [14]. As these start-ups operate with higher research and development uncertainty, this introduces a distinct investment logic and stagewise evaluation. Despite these insights the literature remains fragmented with limited empirical clarity of how VCs adjust evaluation frameworks for AI-specific risks including data governance, model scalability, and algorithmic performance uncertainty. This indicates insufficient integration of AI technological realities into VC investment theory.

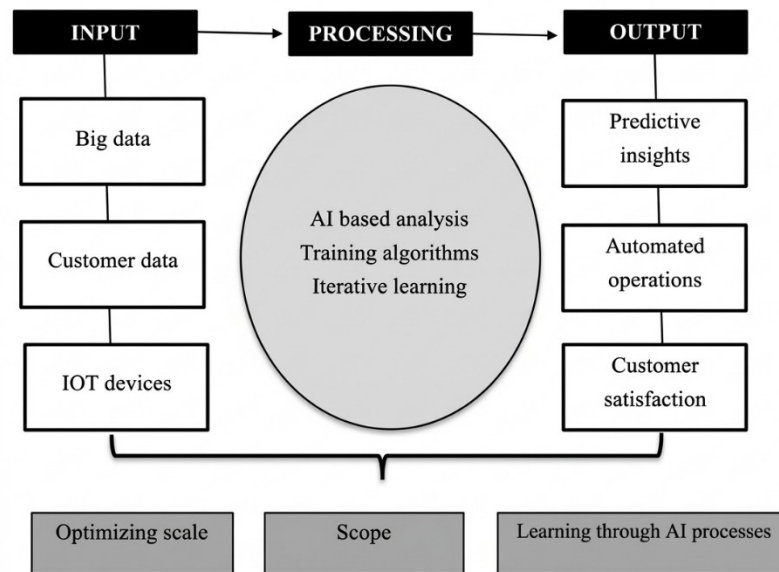


Figure 1. AI factory approach for AI-driven tech start-ups

### 2.3. Risk factors in VC investment in AI driven tech start-ups

Lin [16] highlighted the role of VC in fostering sustainable economic development, however, literature identifies multiple risk factors, including economic, political, and financial risks, whose impact on VC remains largely unexplored [17]. VC adopt heterogeneous evaluation approaches, particularly in assessment of entrepreneurial teams, combining intuitive judgement with structured and analytical evaluations mechanisms [18]. In the context of AI start-ups, specialized technical expertise and contextual factors such as geographic disparities further shape investment assessment processes, while funding remains highly selective with only 3-4 start-ups from over 500 proposals are funded [19]. VC model requires staged investment cycles and interruptions can cause operational failure [15]. Weber *et al.* [14] identified technology related risks, associated with developing and implementing AI solutions, including potential algorithmic biases and errors, scalability challenges, and concerns regarding the quality and availability of data. Despite these contributions, current VC risks primarily categorize into market, product, managerial, financial and insufficiently integrate AI-specific technological and data-related risks. Compared with existing VC investment framework by Gompers *et al.* [20] which emphasizes pre-investment screening and post-investment monitoring, AI start-ups introduce additional layers of technological and data risks, indicating the need for expanded risks classification for AI start-ups.

### 2.4. Growth stages of AI tech start-ups and VC investment

Previous literature [15], [20], [21] highlighted stages in start-ups concerning VC investment, including: i) seed/early stage for technology experimentation and validation, ii) growth stage with commercialization and initial market adoption, and iii) later/maturity stage with scaling and preparation for initial public offering (IPO)/acquisition. The nature and severity of risks evolve across these stages and indicating heterogeneous VC involvement, shifting from capability-building and technical due diligence to market scaling support and governance oversight. Understanding these stages informs the development of conceptual risk taxonomy. This directly informs the application of a theoretical lens for structured analysis.

## 2.5. Theoretical perspective

Risk management theory focuses on systematic identification, assessment, and management of potential risks that may affect organizational objectives. Although the concept of risk dates back over 2,400 years with early examples from the Athenians. However, risk management as a formal scientific field emerged within the last 30-40 years [22]. Risk management and its application in VC investment remain underdeveloped in management and entrepreneurship literature [23], despite VC investments being inherently high-risk, particularly for start-ups facing liability of newness and higher failure rates. According to ISO 31000, risk management is a continuous cycle of risk identification, assessment, treatment, and monitoring with risk evolving over time and across stages. ISO 31000 grouped risk identification, analysis, and evaluation under risk assessment [24], and classified risks into strategic, financial, operational, technological, legal or regulatory, and reputational categories. The two core propositions, including the risks evolving over time and the classifying risks into broader categories, lead to decision making, providing the theoretical foundation of this study.

While ISO 31000 provides the primary lens for risk identification and evaluation, AI-driven start-ups operate within specialized technology development lifecycles that introduce dynamic uncertainties. Frameworks such as cross-industry standard process for data mining (CRISP-DM) [25] and AI factory [12] shows how risks emerge across data acquisition, model development, deployment, and continuous improvement, quality, algorithmic bias, model drift, explainability and operational reliability. In this review, risk management theory structures and categorizes risks identified in the literature in alignment with RQ1 and RQ2, using a lifecycle and process-oriented approach to explore how risk perception shifts across growth stages of AI tech start-ups. Guided by ISO 31000 principles, a conceptual map on Figure 2 illustrates how risk identification and assessment processes guided the classification of risks and how these evolve across the life cycle of AI-driven start-ups and ultimately influencing VC decision making.



Figure 2. Conceptual map of risks across VC investment and AI start-ups growth stages

## 3. METHOD

This study followed the SLR approach to identify the risk variations that influence VC investment decisions in AI-driven tech start-ups. Moher *et al.* [26] used preferred reporting items for systematic reviews and meta-analysis (PRISMA) guidelines. The review includes the following steps.

### 3.1. Topic identification and selection of relevant literature

This study conducted with a systematic approach guided by the PRISMA guidelines [27], [28] to ensure thorough identification and review of published studies to identify risk variations influencing VC investment decisions in AI-driven tech start-ups. The search strategy focused on VC investment risks, funding stages, and risk mitigation, synthesizing peer-reviewed journal articles and conference proceedings published between 2019-2024 with a focus on those that discuss VC investment in AI tech start-ups. The timeframe reflects the period of intensified in AI technologies and acceptance with increased funding interest, increased start-up activity, the growing VC interest following advances in AI models. Search was performed across four academic databases, including IEEE Explore, Web of Science (WoS), Scopus, and ProQuest, selected for their broad coverage of technology, entrepreneurship, and investment research. Keywords included “venture capital”, “AI-startups”, “deep technology”, “investment risks”, “growth stages”, “seed stage”, “maturity stage”, venture capital risks”, and “risk mitigation”. Inclusion criteria covered academic and conference publications addressing VC investment decisions, risk factors, and AI start-ups activity, while studies unrelated to VC investment risks, AI technology, or funding strategies were excluded. To ensure consistency in risk identification, a structured classification logic was applied, informed by established VC and risk management typologies. Risks were organized into mutually exclusive categories, including technological, financial, operational, market, regulatory and exit risks. Any risk related to product-market fit or customer adoption was coded as market risks. ISO 31000 informed the process logic of

risk tagging and interpretation, enabling systematic synthesis across studies. This review positions itself at the intersection of AI entrepreneurship and VC investment by examining how AI-related risk categories evolve across start-up stages. The process of screening relevant studies is illustrated in Figure 3 of the PRISMA diagram.

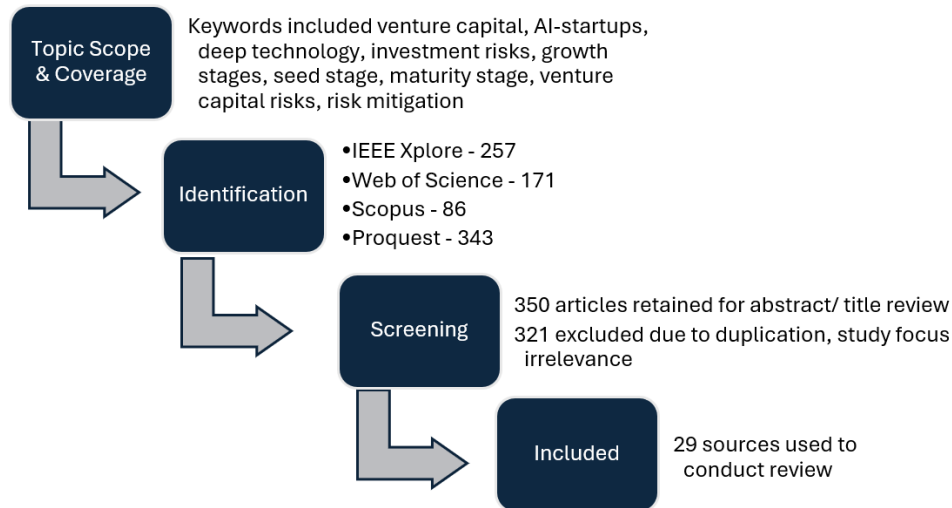


Figure 3. PRISMA diagram of search strategy

### 3.2. Screening of studies

An initial pool of 857 articles was retrieved using the defined search strings and selection criteria. During the initial screening, duplicates and clearly unrelated studies were removed, resulting in 350 articles retained for title and abstract review. Subsequent eligibility assessment involved full text to ensure alignment with VC involvement in AI-focused start-ups and discuss of risk related factors. Studies that failed to meet criteria were excluded. Following the screening process, among 350, a total of 321 studies were excluded due to duplication, thematic irrelevance or insufficient academic rigor, leaving 29 studies for final inclusion. These 29 studies comprised journal articles and conference papers that provide diverse perspectives on risk and investment considerations in AI driven entrepreneurial ventures. These 29 sources as shown in Table 1 formed the basis for synthesis and analysis in this review.

### 3.3. Data synthesis and analysis

This phase involved three systematic procedures to facilitate a comprehensive analysis of the selected studies: data extraction, synthesis, and reporting.

#### 3.3.1. Data extraction

A structured data extraction was used to systematically collect relevant information from each of the 29 selected studies. The extracted data included author(s), year of publication, study objectives, abstracts and key conclusions. This step ensured consistency in data handling and enabled a reliable comparison of diverse study findings.

#### 3.3.2. Data synthesis

The collected data were synthesized using a thematic analysis approach through a structured data extraction process. It was applied to identify recurring patterns and concepts, which were grouped into categories corresponding to the research questions. Themes were constructed around risk factors in VC investment decisions for AI-driven tech start-ups, types of risks, risk factor identification at different growth stages. A hybrid coding approach combining inductive and deductive coding strategies was used, with initial mutual coding followed by refinement using NVivo 15 software. To ensure coding transparency and traceability, a structured coding matrix was applied in NVivo 15, with outputs, including the codebooks, case classifications, and matrix coding queries used to validate consistency and provide an auditable analytical trail, as illustrated in Figure 4.

Table 1. Summary of included studies

Authors/Year	Study focus	Risks category
Haleem <i>et al.</i> (2022) [29]	AI potential for marketing, data management capabilities, designing intricate and advanced algorithms, and transformation for marketing.	Marketing risks
Zeng <i>et al.</i> (2023) [17]	Investigated the influence of economic, political, and financial risks on sustainable VC and the role of human capital in US economy.	Marketing risks
Sangani (2023) [5]	VC analysis, highlighting unique characteristics, importance, and differentiating investment strategies from the viewpoint of investors and investees, motivation factors by VCs opportunities, including scalability, sources, vision, market potential, and technology and management teams.	Operational, Performance risks
Somaya and You (2024) [30]	Phenomena of valued start-ups, venture scalability and VC funding availability start-ups IPO valuations and timing, governance and regulatory burdens.	Operational, Exit risks
Guo and Jiang (2022) [31]	Impact of VC investment of firms, VC-backed firms outperform non-VC-backed in patenting activities, new product sales.	Operational risks,
Tyagi and Gupta (2022) [6]	VC risks, measures to control/ mitigate such risks.	Market, operational, financial, technology, performance
Blume and Hsueh (2024) [18]	Opening the black box of VC' evaluation of entrepreneurial teams	Performance, technology, market, financial risks
Gompers <i>et al.</i> (2020) [20]	Prescreening investment risks, VCs focus on jokey (team) and horse (business model/ product)	Market, financial risks
Limar (2023) [32]	Critical role of effective management in managing startups, exploration of startup ecosystem, venture investment and strategic responsibilities of management.	Operational, Financial, Performance risks
Criado <i>et al.</i> (2024) [33]	Ethical and governance issues to digital innovations developments like AI, role of investment community in technology innovation.	Technology, Regulatory risks
Guernsey <i>et al.</i> (2021) [34]	Mechanisms used by VCs to monitor investments in startups that use trade secrets to protect their intellectual property.	Technology risks
Pu (2022) [35]	Legal nature of algorithms, ethical dilemma AI algorithm rights ownership and property protection.	Operational, Technology risks
Pakšytė and Jurevičienė (2022) [36]	Criteria of VC investment including years in business, no. of employees, the marketing strategy.	Market Risks, Financial risks
Yi <i>et al.</i> (2021) [37]	VC contribution in open innovation through three mechanisms: increasing monetary funds, improving absorption capacity, and strengthening executive incentives.	Financial, Performance risks,
Muathe and Otieno (2022) [38]	Role of Kenya's incubator and accelerators in start-up growth but suffers due to weak knowledge-building, inadequate market research, poor customer service, adequate personal training, inefficient demand forecasting and analysis.	Financial risks
Barg <i>et al.</i> (2021) [39]	Emphasize fair-value multiples by comparing the firm value at the time of financing with the firm value at the time of exit.	Financial risks
Soni <i>et al.</i> (2020) [11]	Impact of AI from research and innovation to market deployment, and highlight challenges of trust, ethics, bias, talent shortage.	Technological risks
Åström <i>et al.</i> (2022) [40]	Identified value creation and value capture for AI business model innovation and commercialization with framework phases of identifying prerequisites for AI value creation, matching value capture mechanisms, developing AI business models.	Technological, Performance risks
Climent <i>et al.</i> (2023) [41]	Focuses on how start-ups use ML technology to create an appropriate value, early-stage funding to develop strategies, funding outcomes.	Performance risks
Gouda and Tiwari (2021) [42]	Highlight that knowledge management, climate for innovation, learning agility and internal corporate communication positively affect innovation adoption.	Performance risks
Hutchinson (2021) [43]	Introduced concept of 'self-innovative artificial intelligence (SAI) in which organizational utilization of AI with advancing existing or new products, enhance innovative offerings.	Performance risks
Shahriar <i>et al.</i> (2023) [13]	Introduced unique threats to privacy and ethical processing and protection at each stage of AI life cycle, categories of privacy risks including identification, inaccurate decision, non-transparency, non-compliance with privacy regulations.	Regulatory risks
Crockett <i>et al.</i> (2023) [44]	Focused on legal, social, ethical, public opinion to build trustworthy AI solutions, mechanisms for small- and medium-sized enterprises (SMEs) to focus on conceptualizing stages of AI life cycle.	Market, Financial, Regulatory risks
Cobbe and Singh (2021) [45]	Role of AI as a service (AlaaS), its processing chains in data protection law, and its illegal use.	Regulatory risks
Cumming <i>et al.</i> (2023) [46]	Foundational themes in VC research as VC adoption and financing processes, VC roles in business, VC governance, VC syndication and creation of public organizations.	Exit risks
Lin (2022) [16]	Proposed a dualist approach towards facilitating the development of sustainable VC funds and to craft a role for regulators that facilitates the simultaneous availability of several factors in a sustainable VC cycle (fund raising to exit).	Exit risks
Siddiqui <i>et al.</i> (2021) [8]	VC challenges in Saudi Arabia including lack of government support, bureaucratic procedure concerning VC. Further VC challenges into six groups including entrepreneurial ecosystem, culture, attitudes, mindset, finance, and planning.	Exit risks
Reilly <i>et al.</i> (2022) [47]	Highlighted United Kingdom antitrust policy on merger review and how it impacts acquisition of start-ups and evaluation merits by VCs.	Exit risks
Bessière <i>et al.</i> (2020) [48]	Explore concept of complex funding and impact on dynamic of nascent venture governance.	Regulatory risks

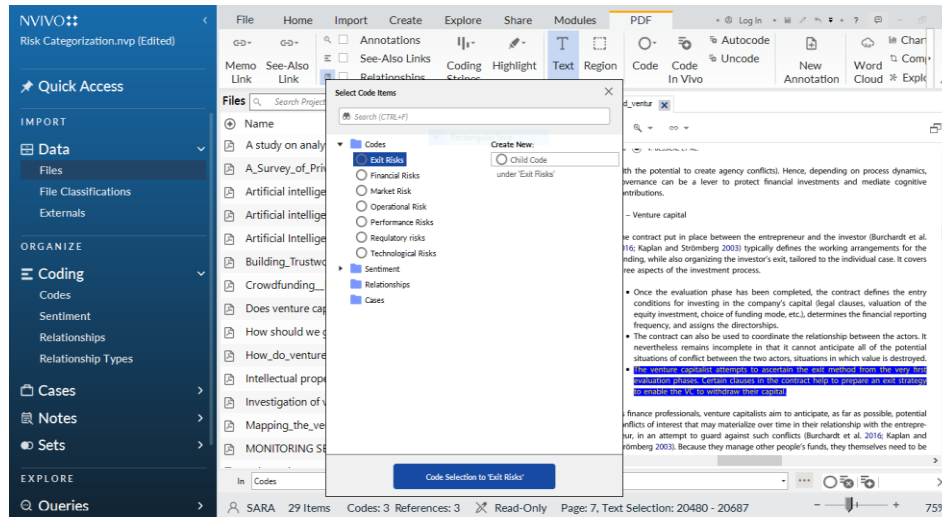


Figure 4. Coding used for thematic analysis using NVivo 15

### 3.3.3. Reporting

A narrative synthesis approach was adopted to systematically present and interpret the outcomes of the thematic analysis. This approach enables the integration of patterns and identified themes. NVivo 15 was used to support qualitative coding and to ensure systematic exploration of the data.

### 3.4. Quality appraisal and bias consideration

Consistent with SLR practices in management and entrepreneurship research, quality assurance was embedded through thorough source selection and structured screening procedures. This study aligned with PRISMA guidelines and incorporated quality safeguards suitable for social science evidence synthesis. The quality was indirectly considered by selecting only peer-reviewed journal articles and conference papers indexed in Scopus, WoS, IEEE, and ProQuest which are widely recognized for their academic accuracy.

## 4. RESULT AND DISCUSSION

This section presents the synthesized findings from the SLR of 29 selected studies, focusing on VC risks affecting AI tech start-ups with a specific focus on variations in these risks across different growth stages. The analysis outlines key VC risk types, followed by an examination of specific risk categories that emerge during the seed, growth, and maturity stages of AI start-ups with reference to investment. A synthesized matrix is then developed to systematically categorize stage-specific risks. A narrative synthesis supported by thematic analysis was used, with NVivo 15 applied to ensure systematic qualitative coding.

### 4.1. Risks affecting VC investment in AI

VC investment has surged over recent decades due to its advantages over other financing options. According to Liu [49], one key benefit is access to substantial financial resources that are often inaccessible through conventional funding channels. However, VC investment decisions involve several risks factors with external uncertainties and internal industry dynamics [6]. To structure the discussion of risks, this review organizes them into seven key categories identified in the literature, including market, operational, financial, technological, performance, regulatory and legal, and exit risks. The following subsections explore each category, highlighting their relevance to VC investment in AI-driven tech start-ups.

#### 4.1.1. Market risks

Market risk refers to failure to survive when shifts in consumer preferences affect a company's growth. VC investments are exposed to market risks such as sector volatility, currency fluctuations, interest rates, and valuation challenges that influence exit value [6]. For AI-driven tech start-ups, this risk is heightened due to rapid technological change and evolving market adoption of AI-based solutions [44]. Market risk also includes fluctuations in demand with reference to AI applications for marketing and segmentation [6], competitive pressures and broader economic conditions [17], which can quickly alter market dynamics and challenge AI start-ups' growth and technological relevance. Gompers *et al.* [20] emphasize that the shift in consumer preferences and technological advancements can rapidly alter market dynamics and pose significant challenges for start-ups.

#### 4.1.2. Operational risks

This risk arises from internal inefficiencies, management issues and failures in execution, which hinder the effective execution of business plan. Operational risks stem from internal factors such as management capabilities, execution challenges, and operational inefficiencies [6]. In AI-driven tech start-ups, operational risks include algorithmic inaccuracies, system downtime pose significant risks to enhance reliability and safety of AI models [35]. Data dependency is another risk where start-ups can turn this into advantage by developing proprietary datasets or creating data-driven products distinct from market [31]. Scaling issues come under major operational risk and can impede growth and relations with VC investors [15] are not just a risk but also opportunity for AI start-ups. Additional operational risks stem from dependency on third-party technologies, data providers, and lack of strategic partnerships and collaborations [32].

#### 4.1.3. Financial risks

It involves poor financial management and liquidity issues that may lead to collapse and bankruptcy [36]. It includes challenges related to funding availability, cash flow management and financial stability, with liquidity risk arising from long-term lock-in periods and absence of an active secondary market, limiting exit timing and returns predictability [6]. In AI-driven tech start-ups, financial risk intensified by high capital cost for research and development due to the complex nature of AI technologies [37], often combined with delayed revenue generation and extended timelines to profitability, which increase liquidity risks [38]. VC investors also face valuation related risks linked to fair-value investment, investment multiples, consortium size, investor experience, exit strategies, and financing stage that result in value fluctuations between financing and exit [39]. Also, agency risk in VC arises from information asymmetry and limited oversight where founders may act in their own interest under conditions of uncertainty and incomplete information [6]. In addition, AI start-ups face extended timeline to profitability and delayed exits due to long gestation periods to refine their technologies and achieve market acceptance, delaying potential exit and returning for investors [20], [39]. While rapid technological advancements and evolving market trends, financial risks emerge where start-ups struggle to capture sufficient market share amidst changing conditions [32].

#### 4.1.4. Technology risks

This risk arises from uncertainties in product development, technological advancements, and intellectual property protection [6], with AI start-ups facing knowledge obsolescence, changing market preferences, and fluctuating investment cycles such as AI winters which reflect uncertainty in technological trends. Despite growing investor interest, deep learning algorithms may produce unreliable outcomes, while challenges related to explainability, ethics, bias, trust, talent shortage that hinder the reliable and scalable development of AI solutions [11], [44]. Legal nature of algorithms and intellectual property disputes [35] that impact their competitive advantage and market position. AI evolves swiftly with breakthroughs and advancements that continually reshape industry standards and competitive dynamics. Studies [33], [40] emphasized that AI start-ups face technology risks when becoming outdated or superseded by advanced solutions, undermine market position, and value proposition. AI value creation depends on capable networks that assess internal AI maturity, infrastructure, industry readiness and value creation potential [40], where gaps create significant technology risks. AI tech start-ups also face technological feasibility and scalability risks, as AI algorithms and models may perform unpredictably across datasets and environments. Cyber security and data are critical technological risks that affect asset security, valuation, and regulatory compliance particularly under general data protection regulations (GDPR). Issues such as algorithmic bias and fairness are generally viewed as technical shortcomings rather than ethical problems [33]. Protecting proprietary algorithms, patents and trade secrets from unauthorized use or imitation is essential for competitive advantage and VCs seek assurance of adequate IP strategies and safeguards to mitigate these risks [34].

#### 4.1.5. Performance risks

It is related to the performance capabilities of start-up leadership, team building, and cohesion, which directly influence innovation outcomes. AI start-ups require scarce and expensive specialized talent from relevant industries, particularly in areas such as NLP technologies like those developing AI Chatbots need experts in ML techniques [40] and innovative performance [37]. AI start-ups can create and capture value the factors related to novelty and expectations of efficiency and performance. Performance indicators include productivity, profitability, cost reductions and inventory reduction with competitive advantage [41], but attracting and retaining talent remains challenging and affects operational efficiency. Gouda and Tiwari [42] emphasized that talent agility and innovation are crucial for firms transitioning from Industry 3.0 to 4.0. In early 2000s, talent agility linked to psychological empowerment, though its enablers remain limited. Innovation adoption depends on employees' acceptance and usage of new technologies, involves employees attitude formation, decision making, and corrective actions for successful implementation. Hutchinson [43] introduced 'self-innovating artificial intelligence (SAI) defined as organizational utilization of AI to advance

existing or developing new complex products. The complexity of AI innovation leads to technical setbacks, extended timelines, and increased resource consumption, leading VC investors to closely assess team management, technological acceptance, and market viability of start-up innovation [32].

#### 4.1.6. Regulatory and legal risks

It involves adverse changes in laws and regulations that impose additional costs or restrict operations, arising from uncertainties in regulatory frameworks, legal requirements, and industry standards [6]. AI start-ups operate within complex regulatory environments, where evolving regulations influence the design and development of AI systems and require compliance with data privacy, algorithmic accountability, and ethical use principles [48], [13]. Crockett *et al.* [44] discussed EU Regulatory Framework on AI with four risk levels, including i) unacceptable risks that is threat to safety, livelihood, and rights of people; ii) high risk which is law enforcement, broader control management, high quality datasets, clear explainability protocols to users, high levels of robustness, security, and accuracy; iii) limited risk include chatbots where human and machine transparency is needed; and (iv) minimal risk based on applications like AI enabled spam filters and video games. Rapid AI development places SMEs and small ventures in regulatory grey areas with unclear legal guidelines, leading to legal disputes and delays in product launches [44]. Changes in regulations introduce compliance costs and restrict market opportunities, affection financial projections and growth potential of AI start-ups [33], [45].

#### 4.1.7. Exit risks

VC aims to exit through IPOs, public offerings, acquisitions, or secondary sales, but market conditions, timing and valuation uncertainties, and the lack of credible sustainability benchmarks affect exit opportunities and returns [30]. As highlighted by Lin [16], the absence of a specialized sustainability board and standardized sustainability disclosure and regulatory clarity undermines investor confidence at the exit stage. To mitigate these risks, regulatory support is needed for reliable impact rating agencies and transparent reporting, ensuring viable and trustworthy exit options for investors. Siddiqui *et al.* [8] pointed out the regulatory environment, capital controls, and firm's ownership structures further complicate exits. Proposed changes in global merger review policies, such as those by UK antitrust regulator, increase scrutiny, costs, and review times creating exit risk for start-up acquisition. As acquisition is a key VC exit route, these regulatory shifts may dampen investor incentives and hinder entrepreneurial growth by delaying efficient exits [47].

This SLR identified and categorized risks from 29 studies into seven major categories, including market, technological, financial, operational, performance, regulatory, exit risks. In response to RQ1, technological and operational risks were most frequently cited at 9/29 (31%) each, followed by financial risks at 7/29 (24.1%). Market, performance, and regulatory risks appeared in 6/29 (20.6%), while exit risks were least appeared and in only 5/29 (17.2%) studies as presented in Table 2.

The analysis revealed interdependencies among risk categories and highlighted that technological risk such as data quality and model stability usually contributed to regulatory risk, as non-compliant AI systems increase revelation to legal analysis. Market risk closely intertwined with financial risks with uncertain product-market fit leads to revenue volatility that affects fundraising capacity in early stages. Further operational risks including lack of talent and infrastructure limitations, exacerbate performance risks. These interdependencies emphasize that risks do not develop in isolation but strengthen each other across growth stages. This highlights the need for integrated risk assessment at growth stages.

Table 2. Frequency of risk categories across included studies

Risk category	Number of studies (n)	Percentage (%)
Technological	9	31
Operational	9	31
Financial	7	24.1
Market	6	20.6
Performance	6	20.6
Regulatory and legal	6	20.6
Exit	5	17.2

## 4.2. Risk factors identification at different growth stages

According to Liu [49], although global VC showed substantial growth before 2021, however, regarding VC investment trends and risk factors at different growth stages, early-stage VC activity remained strong in Q2 in 2023. Despite a lower overall increase in VC fund formation compared to previous levels, seed and series A deals still comprised half of all VC transactions, raising \$7.2 billion. This trend is partly due to some funds not yet deploying their previously raised capital. There are certain risks identification VC investment in AI tech start-ups at different growth stages.

#### 4.2.1. Seed and early stage

At the early stage, AI-driven start-ups face heightened technological, financial, marketing and operational risks due to limited resources, unproven products, and underdeveloped business models. Technology risk is especially pronounced, as early-stage AI start-ups often lack proven functionality, scalability and strong datasets, adequate computing infrastructure, increasing the likelihood of technical failure [36]. These technical concerns are particularly critical in AI start-ups because ML models typically require substantial high-quality training data and computational power resources that early-stage start-ups may not yet possess. Early-stage start-ups remain in experimentation and R&D phases, where uncertainty around AI algorithm feasibility, explainability, and ethical ambiguity can delay product development commercialization. These stage-specific risks collectively create a high-risk investment environment for VCs. Financial risk is significant at the early stage as start-ups lack stable revenues and rely on external capital, with high burn rates and capital-intensive AI development cycles increasing uncertainty [38], [39]. At the early stage, with business models still forming, and unclear monetization strategies, lack of liquidity, and valuation uncertainty further increase risks for VCs [6]. Operational risks emerge from limited human resources [50], lack of internal controls and early-stage founders' inexperience in managing growth and attracting key talent [30]. Market risks include unclear customer demand, undefined market segments and fast-changing external environments that may render early assumptions invalid [29], [38]. Early-stage start-ups operate on hypotheses rather than validated market evidence, making VCs rely on founding team's vision and agility. Exit concerns like scalability, readiness for acquisition and IPO are secondary to evaluating product viability and market fit in the initial phase.

#### 4.2.2. Growth stage

At this stage, start-ups typically experience rapid expansion, increased funding rounds and broader market entry while facing evolving risks as they transition from early-stage experimentation to operational execution and market consolidation. Technological risks may lessen, but AI model explainability, bias, and privacy remain critical and regulatory concerns, particularly in contexts of framework like GDPR [33], [40]. Financial risks at this stage involve cash flow volatility, revenue predictability, and pressure to meet performance milestones, intensified by investor expectations and scale-up costs [18], [20], [32]. This stage reflects a shift from securing funding to demonstrating financial sustainability and justifying increased valuations. Operational risks intensify as start-ups face organizational complexity, the need for scalable infrastructure and service delivery, formalized processes, hiring, and systems integration [30]. Market risks shift from product-market fit toward competitive positioning, changing customer preferences, and macroeconomic influences in a more saturated market [32]. Along with this cyber security [33] and compliance risks grow with increased data and customer interactions managed during scale-up [32], particularly with user-facing AI applications. VCs focus on scalability, governance, and sustainable growth, ensuring portfolio companies remain operationally strong and complaint [37], while maintaining innovation.

#### 4.2.3. Maturity/later stage

In the maturity stage, risks increase due to increased pressure to scale operations, meet revenue expectations and prepare for exit such as acquisition and IPO [47]. Regulatory and legal risks intensify with greater market visibility, requiring compliance with data governance, cyber security, IP laws [35]. Failure to comply with emerging AI regulations such as European Union (EU) AI Act [44] and the GDPR, and ethical concerns like algorithmic bias, data privacy, and fairness in automated decision-making systems [13], [33] also included as regulatory and legal concerns at this stage. Legal uncertainties around cross-border data flows and AI accountability further complicate global expansion and impact investor confidence and exit valuations [33], [40]. Exit related risks become more prominent in the maturity phase as investors evaluate the return feasibility, with liquidity constraints, and extended timelines to reach profitability can delay exit opportunities [6], [30]. Technological obsolescence further complicates exit strategies with efficient AI models render existing solutions outdated [47]. Operational risks with scaling challenges and partnership dependencies, reliance on cloud infrastructure, third-party data providers, and strategic alliances increases [32], introducing new vulnerabilities if these relationships are mismanaged or fail to deliver expected value. Operational complexity grows with larger customer bases and multiple geographies, demand a high degree of coordination and resource allocation [51] to balance growth and cost efficiency. Financial risks such as cash flow instability, unbalanced burn rates, and scare external funding remain critical during macroeconomic shifts [32]. The long gestational of AI innovation and pressure for sustainable profitability intensify investor concerns and delay financial returns [18], [20]. VCs must assess both business scalability and financial resilience to adapt to developing market conditions.

The classification of VC risk factors across seed, growth, and maturity stages of AI-driven tech start-ups was systematically derived through thematic synthesis of 29 studies, shown in Table 3. Market risks appeared in 6 studies (20.6%), notably in seed stage for undefined segments [29] and in the maturity stage for

market saturation [32]. Operational and technological risks were the most cited (9/29), 31%), with operational risks concentrated in the growth stage because of infrastructure and service delivery [30], and in maturity stage due to partner dependencies and resource allocation [51]. While technological risks dominated seed and growth stages due to product immaturity and regulatory concerns around explainability [11], [44], shifting to technological obsolescence [47]. Financial risks were indicated in 7 studies (24.1%) with emphasis unstable revenues and external funding reliance [47] in seed stage and cash flow volatility and acquisition challenges in later stages. Performance and regulatory risks were each mentioned in 6 studies (20.6%), intensifying from early ambiguity to maturity stage pressure linked to GDPR compliance, algorithmic bias, and data governance [33], [40]. Finally, the exit risks were least discussed 5/29 (17.2%), and largely confined to the maturity stage, focusing on valuation, acquisition, and IPO challenges [47].

Table 3. Synthesized taxonomy of VC risks across growth stages in AI-driven tech start-ups

Risk variation	Growth stages		
	Seed and early stage	Growth stage	Maturity or later stage
Market risks	Unclear customer demand, undefined market segments, rapidly changing environments [38].	Competitive positioning, changing customer preferences, macroeconomic influences [33].	Market saturation, evolving customer demands, volatility in external environment affecting scalability and exit valuation [39], [47], liquidity constraints [6], [11], [38].
Operational risks	Limited human resources [39], founder inexperience, weak internal controls [11], and retaining talent [11].	Increased organizational complexity, scalable infrastructure and service delivery [11].	Scaling challenges, partnership dependencies, reliance on cloud infrastructure, third-party data providers and increased strategic alliances [33], operational complexity with cost efficiency, demand for high degree of coordination and resource allocation [32], [51].
Financial risks	Lack of stable revenues, dependence on external capital, high burn rates and capital-intensive development cycles worsen financial value [38], [52], liquidity issues, difficulty in estimating valuations [6].	Cash flow volatility, revenue predictability, performance pressures, expectations for scale up costs [33], [43], [52].	Cash flow instability [33], delayed financial returns [43], [52].
Technology risks	Lack proven functionality, scalability, technical uncertainties related to the development and feasibility of AI models and algorithms, delayed commercialization [32].	AI product issues related to AI model explainability, bias, and privacy continue to pose ethical and regulatory concerns particularly in contexts of framework like GDPR [39], [47].	Unpredictability of technological obsolescence, existing outdated solutions [47].
Performance risks	higher ambiguity on founding team vision [38], [53]. How resilient is venture-backed innovation? evidence from four decades of US patenting.	Firms deal with organizational complexity [11].	Pressure to scale, meet revenue expectations [47].
Regulatory risks	AI models explainability and ethical ambiguity [38], [39]	Cyber security [39], compliance risks at scale-up [33], innovation complaint [37].	Visible and subject to compliance with data governance, cyber security and intellectual property laws [35], scrutiny from regulatory authorities, ethical concerns like algorithmic bias, data privacy, and fairness in automated decision-making systems [13], [39], failure to comply with emerging AI regulations (EU AI and GDPR) [44], noncompliance result in reputational damage [39], [47].
Exit risks	Low consideration at this stage, however liquidity challenges [6]	Emerging concerns about long-term scalability, readiness for acquisition and IPO [30].	Realizing returns, potential exit strategies with acquisition and IPO [47], unpredictability of technological obsolescence complicates exit strategies [47].

These findings demonstrate how VC risks evolve across growth stages, with early emphasis on technological feasibility, market acceptance, and strength of founding team. At growth stage, risks shift towards scaling, talent retention, operational inefficiencies, and financial structuring, whereas maturity stage risks combine with regulatory compliance, market saturation, and exit strategies. From a risk management perspective, the stage-specific distribution of risks provides a structured basis for aligning VC investment strategies, with early-stage focus on team vision and technical potential while later-stage emphasize scalability, governance and regulatory fit. Guided by risk management theory and ISO 31000 principles, this

study integrates lifecycle-based risk assessment, where risk identification, analysis, and evaluation are combined into investment decision-making processes. To strengthen conceptual alignment, the ISO 31000 lens can be viewed in parallel with Enterprise Risk Management (ERM), supports a holistic, and adaptive risk postures for AI start-ups. The study offers a structured taxonomy that categorizes VC risks across seed, growth, and maturity stages in AI-driven tech start-ups, incorporating AI-specific factors. The proposed taxonomy contributes to exiting literature by i) providing a lifecycle-based mapping of VC risks, ii) incorporating AI-specific factors such as data dependency, algorithmic scalability and ethical regulatory concerns, and iii) aligning risk categories with practical investment decision points. To the best of author’s knowledge, this is among the early SLR explicitly mapping VC risk evolution in AI start-ups. For VC firms, the findings highlight stage-appropriate risk assessments to improve decision making accuracy, deal structuring, and portfolio risk exposure. For policymakers, taxonomy informs supportive regulatory frameworks targeting AI compliance, data access and talent acquisition during scaling of tech start-ups.

Limitations and future research: this study acknowledges limitations, including lack of formal quality appraisal and empirical validation through real-world cases and longitudinal VC observations. Future research should apply scenario-based analyses, involve investors, AI owners, engineers, data scientists, and examine AI governance frameworks such as Organization for Economic Co-operation and Development (OECD) AI principles, the National Institute of Standards and Technology (NIST) AI risk management framework, and EU AI Act, and empirically test risk categories with tools for real-time VC risk assessment and mitigation.

**5. CONCLUSION**

This systematic review offers a comprehensive view of risk factors influencing VC investment in AI-driven tech start-ups across growth stages by categorizing risks into the market, operational financial, technological, performance, regulatory, and exit. The stage-based taxonomy matrix provides a practical tool for both researchers and practitioners to do more structured lifecycle risk analysis and contributes to VC risks theory by linking governance, ethical, and technical AI considerations in investment strategy. Future research should empirically test these risk categories and develop data-driven, adaptive risk assessment approaches to support sustainable VC investment decisions and inform policymakers and ecosystem enablers in designing effective support mechanisms and regulatory frameworks for AI tech start-ups.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ditng

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

**CONFLICT OF INTEREST STATEMENT**

Authors state no conflict of interest.

**DATA AVAILABILITY**

Data availability is not applicable to this paper as no new data were created or analyzed in this study.




## REFERENCES

- [1] M. Shirer, "IDC: artificial intelligence will contribute \$19.9 trillion to the global economy through 2030 and drive 3.5% of global GDP in 2030," *International Data Corporation*, 2024. Accessed: Jun. 4, 2025. [Online]. Available: <https://my.idc.com/getdoc.jsp?containerId=prUS52600524>
- [2] S. Kaggwa, A. Akinoso, S. O. Dawodu, P. U. Uwaoma, O. J. Akindote, and S. O. Eloghosa, "Entrepreneurial strategies for AI startups: navigating market and investment challenges," *International Journal of Management and Entrepreneurship Research*, vol. 5, no. 12, pp. 1085–1108, Dec. 2023, doi: 10.51594/ijmer.v5i12.662.
- [3] A. Brem, F. Giones, and M. Werle, "The AI digital revolution in innovation: a conceptual framework of artificial intelligence technologies for the management of innovation," *IEEE Transactions on Engineering Management*, vol. 70, no. 2, pp. 770–776, Feb. 2023, doi: 10.1109/TEM.2021.3109983.
- [4] O. A. Farayola, A. A. Abdul, B. O. Iboror, and E. C. Okeleke, "Innovative business models driven by ai technologies: a review," *Computer Science and IT Research Journal*, vol. 4, no. 2, pp. 85–110, Nov. 2023, doi: 10.51594/csitrj.v4i2.608.
- [5] D. R. Sangani, "A study on analysis of venture capital financing," *Journal of Management Research and Analysis*, vol. 10, no. 2, pp. 124–127, Jun. 2023, doi: 10.18231/j.jmra.2023.021.
- [6] A. Tyagi and C. Gupta, "An analysis: venture capital funding private equity investment in india," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4247680.
- [7] E. Griffith, "Investors pour \$27.1 billion into a.i. start-ups, defying a downturn," *The New York Times*, 2024. Accessed: Jun. 4, 2025. [Online]. Available: <https://www.nytimes.com/2024/07/03/technology/ai-startups-funding.html>
- [8] K. A. Siddiqui, M. E. Al-Shaikh, I. A. Bajwa, and O. Alenzi, "Venture capital challenges in saudi arabia," *Entrepreneurship and Sustainability Issues*, vol. 8, no. 3, pp. 291–302, Mar. 2021, doi: 10.9770/jesi.2021.8.3(17).
- [9] L. Floridi, "Why the AI hype is another tech bubble," *Philosophy and Technology*, vol. 37, no. 4, Dec. 2024, doi: 10.1007/s13347-024-00817-w.
- [10] P. Rastogi, "The role of technology in start-ups and small businesses," *Shodhshauryam, International Scientific Refereed Research Journal*, vol. 6, no. 6, pp. 58–65, 2023, doi: 10.32628/SHISRRJ.
- [11] N. Soni, E. K. Sharma, N. Singh, and A. Kapoor, "Artificial intelligence in business: from research and innovation to market deployment," *Procedia Computer Science*, vol. 167, pp. 2200–2210, 2020, doi: 10.1016/j.procs.2020.03.272.
- [12] P. Jia and C. Stan, "Artificial intelligence factory, data risk, and VCs' mediation: the case of bytedance, an ai-powered startup," *Journal of Risk and Financial Management*, vol. 14, no. 5, May 2021, doi: 10.3390/jrfm14050203.
- [13] S. Shahriar, S. Allana, S. M. Hazratifard, and R. Dara, "A survey of privacy risks and mitigation strategies in the artificial intelligence life cycle," *IEEE Access*, vol. 11, pp. 61829–61854, 2023, doi: 10.1109/ACCESS.2023.3287195.
- [14] M. Weber, M. Beutter, J. Weking, M. Böhm, and H. Krčmar, "AI startup business models," *Business and Information Systems Engineering*, vol. 64, no. 1, pp. 91–109, Feb. 2022, doi: 10.1007/s12599-021-00732-w.
- [15] B. Montanaro, A. Croce, and E. Ughetto, "Venture capital investments in artificial intelligence," *Journal of Evolutionary Economics*, vol. 34, no. 1, pp. 1–28, Jan. 2024, doi: 10.1007/s00191-024-00857-7.
- [16] L. Lin, "Venture capital in the rise of sustainable investment," *European Business Organization Law Review*, vol. 23, no. 1, pp. 187–216, Mar. 2022, doi: 10.1007/s40804-021-00238-8.
- [17] Q. Zeng, R. Zhou, and L. Zheng, "Sustainable financial system and capital investment: a novel perspective of us economy," *Economic Research-Ekonomiska Istraživanja*, vol. 36, no. 2, Jul. 2023, doi: 10.1080/1331677X.2023.2170904.
- [18] F. Blume and J. W. -J. Hsueh, "Opening the black box of venture capitalists' evaluation of entrepreneurial teams," *Journal of Small Business Management*, vol. 62, no. 4, pp. 2116–2151, 2024, doi: 10.1080/00472778.2023.2199318.
- [19] M. C. Benzouai and K. Djeflal, "A bibliometric review of research on venture capital," *Asian Academy of Management Journal*, vol. 26, no. 1, pp. 47–88, Jun. 2021, doi: 10.21315/aamj2021.26.1.3.
- [20] P. A. Gompers, W. Gornall, S. N. Kaplan, and I. A. Strebulaev, "How do venture capitalists make decisions?," *Journal of Financial Economics*, vol. 135, no. 1, pp. 169–190, 2020, doi: 10.1016/j.jfineco.2019.06.011.
- [21] G. Weiss, "A theory of seed financing," *University of Illinois Law Review*, vol. 2025, no. 5, pp. 1839–1888, 2025, doi: 10.2139/ssrn.4668015.
- [22] T. Aven, "Risk assessment and risk management: review of recent advances on their foundation," *European Journal of Operational Research*, vol. 253, no. 1, pp. 1–13, Aug. 2016, doi: 10.1016/j.ejor.2015.12.023.
- [23] P. Bromiley, M. McShane, A. Nair, and E. Rustambekov, "Enterprise risk management: review, critique, and research directions," *Long Range Planning*, vol. 48, no. 4, pp. 265–276, Aug. 2015, doi: 10.1016/j.lrp.2014.07.005.
- [24] H. Hamir and R. M. Sum, "An analysis of risk management processes and comparison with ISO 31000:2018," *Asian Journal of Research in Business and Management*, Dec. 2021, doi: 10.55057/ajrbm.2021.3.4.3.
- [25] C. Schröer, F. Kruse, and J. M. Gómez, "A systematic literature review on applying crisp-dm process model," *Procedia Computer Science*, vol. 181, pp. 526–534, 2021, doi: 10.1016/j.procs.2021.01.199.
- [26] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: the prisma statement," *Journal of clinical epidemiology*, vol. 62, no. 10, pp. 1006–1012, 2009, doi: 10.1016/j.jclinepi.2009.06.005.
- [27] M. H. Abbas and M. Bulut, "Navigating the landscape of sustainable entrepreneurship research: a systematic literature review," *Discover Sustainability*, vol. 5, no. 1, Jul. 2024, doi: 10.1007/s43621-024-00293-4.
- [28] K. L. de A. Santos and G. A. Cândido, "Systematic literature review (SLR) on sustainable entrepreneurship and sustainable local development," *Revista de Gestão Social e Ambiental*, vol. 19, no. 5, May 2025, doi: 10.24857/rgsa.v19n5-012.
- [29] A. Haleem, M. Javaid, M. A. Qadri, R. P. Singh, and R. Suman, "Artificial intelligence (AI) applications for marketing: a literature-based study," *International Journal of Intelligent Networks*, vol. 3, pp. 119–132, 2022, doi: 10.1016/j.ijin.2022.08.005.
- [30] D. Somaya and J. You, "Scalability, venture capital availability, and unicorns: evidence from the valuation and timing of IPOs," *Journal of Business Venturing*, vol. 39, no. 1, Jan. 2024, doi: 10.1016/j.jbusvent.2023.106345.
- [31] D. Guo and K. Jiang, "Venture capital investment, intellectual property rights protection and firm innovation: evidence from China," *Entrepreneurship and Regional Development*, vol. 34, no. 5–6, pp. 434–470, May 2022, doi: 10.1080/08985626.2022.2062618.
- [32] V. Limar, "The role of management in fostering startup development with venture investments," *Journal of Innovations and Sustainability*, vol. 7, no. 4, Dec. 2023, doi: 10.51599/is.2023.07.04.11.
- [33] J. S.-Criado, C. M.-Aldeanueva, S. Nardini, C. L.-Pablos, M. Balestrini, and C. S. R.-Torres, "How should we govern digital innovation? a venture capital perspective," *Technological Forecasting and Social Change*, vol. 200, Mar. 2024, doi: 10.1016/j.techfore.2023.123198.
- [34] S. Guemsey, L. P. Litov, and H. Park, "Monitoring secretive startups," *SSRN Electronic Journal*, 2021, doi: 10.2139/ssrn.3940610.




- [35] K. Pu, "Intellectual property protection for AI algorithms," *Frontiers in Computing and Intelligent Systems*, vol. 2, no. 3, pp. 44–47, 2023, doi: 10.54097/fcis.v2i3.5210.
- [36] I. Pakšytė and D. Jurevičienė, "Study on the eligibility of venture capital funds in the united states market," in *12th International Scientific Conference Business and Management 2022*, May 2022, doi: 10.3846/bm.2022.778.
- [37] R. Yi, H. Wang, B. Lyu, and Q. Xia, "Does venture capital help to promote open innovation practice? evidence from China," *European Journal of Innovation Management*, vol. 26, no. 1, pp. 1–26, Jan. 2023, doi: 10.1108/EJIM-03-2021-0161.
- [38] S. Muathe and V. Otieno, "Startup incubation and accelerators in Africa; are start-ups scaling up in Kenya?," *American International Journal of Social Science Research*, pp. 23–28, Apr. 2022, doi: 10.46281/aijssr.v11i1.1688.
- [39] J. A. Barg, W. Drobetz, and P. P. Momtaz, "Valuing start-up firms: a reverse-engineering approach for fair-value multiples from venture capital transactions," *Finance Research Letters*, vol. 43, 2021, doi: 10.1016/j.frl.2021.102008.
- [40] J. Åström, W. Reim, and V. Parida, "Value creation and value capture for AI business model innovation: a three-phase process framework," *Review of Managerial Science*, vol. 16, no. 7, pp. 2111–2133, Oct. 2022, doi: 10.1007/s11846-022-00521-z.
- [41] R. C.-Climent, D. M. Haftor, and M. W. Staniewski, "Using machine learning to create and capture value in the business models of small and medium-sized enterprises," *International Journal of Information Management*, vol. 73, Dec. 2023, doi: 10.1016/j.ijinfomgt.2023.102637.
- [42] G. K. Gouda and B. Tiwari, "Talent agility, innovation adoption and sustainable business performance: empirical evidences from indian automobile industry," *International Journal of Productivity and Performance Management*, vol. 71, no. 6, pp. 2582–2604, Jun. 2022, doi: 10.1108/IJPPM-02-2021-0071.
- [43] P. Hutchinson, "Reinventing innovation management: the impact of self-innovating artificial intelligence," *IEEE Transactions on Engineering Management*, vol. 68, no. 2, pp. 628–639, Apr. 2021, doi: 10.1109/TEM.2020.2977222.
- [44] K. Crockett, E. Colyer, L. Gerber, and A. Latham, "Building trustworthy ai solutions: a case for practical solutions for small businesses," *IEEE Transactions on Artificial Intelligence*, vol. 4, no. 4, pp. 778–791, Aug. 2023, doi: 10.1109/TAI.2021.3137091.
- [45] J. Cobbe and J. Singh, "Artificial intelligence as a service: legal responsibilities, liabilities, and policy challenges," *Computer Law & Security Review*, vol. 42, Sep. 2021, doi: 10.1016/j.clsr.2021.105573.
- [46] D. Cumming, S. Kumar, W. M. Lim, and N. Pandey, "Mapping the venture capital and private equity research: a bibliometric review and future research agenda," *Small Business Economics*, vol. 61, no. 1, pp. 173–221, Jun. 2023, doi: 10.1007/s11187-022-00684-9.
- [47] D. Reilly, D. D. Sokol, and D. Toniatti, "The importance of exit via acquisition to venture capital, entrepreneurship, and innovation," *SSRN Electronic Journal*, 2021, doi: 10.2139/ssrn.3981970.
- [48] V. Bessière, E. Stéphanie, and P. Wirtz, "Crowdfunding, business angels, and venture capital: an exploratory study of the concept of the funding trajectory," *Venture Capital*, vol. 22, no. 2, pp. 135–160, Apr. 2020, doi: 10.1080/13691066.2019.1599188.
- [49] M. Liu, "Growth of venture capital in international markets," *Open Journal of Business and Management*, vol. 11, no. 6, pp. 3237–3254, 2023, doi: 10.4236/ojbm.2023.116176.
- [50] A. Cavallo, A. Ghezzi, C. Dell'Era, and E. Pellizzoni, "Fostering digital entrepreneurship from startup to scaleup: the role of venture capital funds and angel groups," *Technological Forecasting and Social Change*, vol. 145, pp. 24–35, Aug. 2019, doi: 10.1016/j.techfore.2019.04.022.
- [51] A. Ghezzi and A. Cavallo, "Agile business model innovation in digital entrepreneurship: lean startup approaches," *Journal of Business Research*, vol. 110, pp. 519–537, Mar. 2020, doi: 10.1016/j.jbusres.2018.06.013.
- [52] A. S. Gutterman, "Financing the business: a guide for sustainable entrepreneurs," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4256140.
- [53] S. Howell, J. Lerner, R. Nanda, and R. Townsend, "How resilient is venture-backed innovation? evidence from four decades of U.S. patenting," *NBER Working Paper 27150*, National Bureau of Economic Research, 2020, doi: 10.3386/w27150.

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