Gordon Institute of Business Science
University of Pretoria

The influence of artificial intelligence on decision-making in deal selection in private equity

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

03 November 2025

Abstract

This study examines the integration and influence of artificial intelligence (AI) in deal-selection processes within South African private equity (PE) and venture capital (VC) firms. Using theoretical frameworks including Information Processing Theory and Principal-Agent Theory, the research explores how AI enhances decision quality, speed, and uniformity while balancing human intuition and contextual judgment. Findings reveal that AI is primarily used as a supportive analytical tool, aiding in data synthesis, regulatory scanning, and due diligence rather than replacing human decision-making. Although AI has improved efficiency and transparency, challenges such as data scarcity, confidentiality concerns, regulatory limitations, and lack of local contextualization persist. Human discretion remains central, especially in evaluating qualitative factors such as founder integrity and cultural fit. The research emphasizes that AI's current value lies in process improvement rather than financial outcomes. Responsible and context-aware adoption is essential, requiring robust governance frameworks, localized models, and ethical deployment. The study concludes that collaboration among regulators, firms, and industry bodies is vital to build a sustainable AI ecosystem in South Africa's investment landscape.

KEYWORDS

Artificial intelligence; private equity; deal selection; decision making; information processing theory; principal agent theory.

Plagiarism Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Mangwane Mabuza

3 November 2025

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
PE	Private Equity
VC	Venture Capital
LPs	Limited Partners
XAI	Explainable Artificial Intelligence
IPT	Information Processing Theory
AVCA	African Venture Capital Association
IC	Investment Committee

Chapter 1: Introduction to the Research Problem

1.1 Background and Research Context

Artificial intelligence (AI) and machine learning (ML) technologies have evolved rapidly and dramatically changed how decisions are made in various industries, including finance and investment (Ferrati & Muffatto, 2021). To enhance their efficiency, detect new investment opportunities, and control risks in their portfolios, the use of AI-based analysis tools is rapidly increasing among the private equity (PE) and venture capital (VC) firms (Bai & Zhao, 2021). The amount of global financial data has expanded dramatically, driven by digitisation, algorithmic trading, and open banking, with the financial services sector contributing approximately 20% of all enterprise data worldwide (IDC, 2022).

Nevertheless, even though the application of AI in the investment process is increasingly becoming integrated, it is still at an early stage of development. This is especially true for Private Equity (PE) and Venture Capital (VC) firms in emerging markets. Large investment firms like Blackstone and KKR are starting to incorporate artificial intelligence (AI) into their investment operations and are investing large amounts of money in data infrastructure and analytics. To illustrate on this case, Blackstone released that it was investing in a data intelligence firm to the tune of US$300 million to aid in AI and high-performance computing. However, the African private equity market is significantly smaller; for example, the South African one was estimated to be about US$3.53 billion in 2024 (Statista, 2025). Such a difference illustrates that; although AI implementation has become popular worldwide, developing economies still struggle with insufficient infrastructure, data quality, and technological preparedness (Mashile, 2025).

The adoption of Artificial Intelligence (AI) in investment management around the world has largely enhanced the precision and speed of decision-making. The leading front of this transition is developed markets, including the United States and Europe, where AI is becoming more commonly used in predictive analytics, risk assessment, and portfolio optimisation (EQT Group, 2024). Data-driven systems have been embraced by major private equity and venture capital firms in these regions, to help them identify good investments and risk management has become more effective (Deloitte, 2023). However, despite such a development, the implementation of AI in the emerging markets remains at its nascent stage, with an increasing digital and analytical divide

between the developed and developing economies (Statista, 2024). This is more pronounced in the emerging economies such as South Africa. Some of the weaknesses that the South African Private Equity (PE) and Venture Capital (VC) industries are grappling with include small size, small to large transactions, underdeveloped decision-support tools. As per estimation of the Southern African Venture Capital and Private Equity Association (SAVCA, 2025) in 2024, there was approximately R13.35 billion of active venture capital of 1,325 deals in the region out of the global market in the private equity industry. Although South Africa has one of the most developed financial systems on the continent, PE and VC activity in this country continues to suffer a structural limitation, including deal flow centralization and insufficient development of digital infrastructure (SAVCA, 2025). These are problematic and it is time consuming to filter and identify possibilities of viable investments. Based on these constraints, it is opportune and significant to explore opportunities presented as well as the impediments posed by AI to deal sourcing and selection procedures within South-African PE and VC firms. Using AI in the investment decisions can transform the process into a fast, predictable, and data-driven process and improve investment performance overall. Such a study will also help explain how emerging markets can employ digital transformation to boost competitiveness, transparency, and sustainable growth in their financial ecosystems.

1.2 Research Problem

The decision-making process in the frames of the work of the private equity (PE) and venture capital (VC) investment companies is ambiguous and complicated. Fund managers have to deal with numerous investment opportunities with limited, incomplete, quantitative or qualitative information (Bai & Zhao, 2021). Conventional decision-making in the industries under consideration is firmly based on human judgment, intuition, and experience aspects that, although useful, may cause profound cognitive biases and inconsistency (Ferrati & Muffatto, 2021). This bias may lead to non-optimal investment choices, capital allocation inefficiency, or the lack of high-potential opportunities (Tversky & Kahneman, 1974).

Artificial intelligence (AI) has powerful decision-support systems that can address some of these deficiencies. Compared to human analysts, AI models are less time-consuming and more accurate to analyse big data in structured and unstructured formats, reveal hidden correlations and provide predictive information (Csaszar et al., 2024). Using PE and VC, AI will also have the opportunity to enhance due diligence, portfolio diversification, and more consistent and objective decision-making (Huang et

al., 2020). Additionally, machine-learning algorithms have the potential to support the work of investors by modelling the risk and returns, which will facilitate evidence-based and data-driven approaches to investments (Bai & Zhao, 2021).

Nevertheless, the use of AI technology in PE and VC decision-making has its share of benefits, and its application is not as widespread as in developing regions (Kearney, 2024). The obstacles to adoption comprise distrust of AI-generated products, data security and privacy concerns, insufficient digital infrastructure, and insufficient AI expertise within the company (Dwivedi et al., 2023). Moreover, the subjective characteristics of the evaluation of investments, in which factors like entrepreneurial ability, market fit, and team dynamics are critical, complicate the process of the AI system in copying the subtlety of human intuition (Ross et al., 2021).

Combining human knowledge and using algorithms to make decisions poses critical theoretical and practical questions as a way to integrate AI into PE and VC processes. In theory, it begs the study of the effects of AI on the quality of decisions, cognitive bias minimisation, and organisational learning (Rahwan et al., 2019). In practice, it points to the necessity to comprehend the organisational, technological and behavioural factors that contribute to using and successfully utilising AI tools in investment decisions (Jarrahi, 2018).

Although there has been an increasing awareness of Artificial Intelligence (AI) as a game-changing instrument in financial decision-making, its successful adoption in the sphere of Private Equity (PE) and Venture Capital (VC) firms is still a scarce issue, especially in the developing markets like South Africa. The intuitiveness and experience that still are critical to the decision-making processes in such firms also tend to create cognitive bias, inconsistency, and inefficiency. Although AI can be used to improve the process of deal sourcing, due diligence, and portfolio diversification, little empirical knowledge exists about how AI can be utilized to supplement human judgment to enhance the quality and accuracy of investments. This gap explains why research should be conducted on how much AI can be used to enhance decision-making in South African PE and VC settings and what organisational, technical, and behavioral obstacles inhibit its implementation.

Consequently, the research problem of the given study is as follows:

What is the effect of AI-enabled decision-support tools on the selection of deals in PE and VC firms by practitioners, and how is this affected by factors such as adoption, trust, and changes to the quality, speed, and consistency of decisions?

1.3 Justification of the Study

1.3.1 Practical/Business Need

The investment environment for Private Equity (PE) and Venture Capital (VC) firms has become increasingly competitive due to the growing number of market participants, the acceleration of digital transformation, and the demand for faster, data-driven decision-making (SAVCA, 2025). Quick and better investment decisions can generate high competitive advantage. The emergence of AI has turned into the disruption in this field that can enhance the process of deal sourcing, automate due diligence, and make the results of the investment more predictable (Bai and Zhao, 2021). As an illustration, AI technologies may analyse the information on the market and the results of competitors and financial figures in real time to enable investors to make more well-balanced and timely decisions (Kearney, 2024). Moreover, the integration of AI would also help to minimise the operation cost and decrease the human error represented by prejudice or a small portion of the data interpretation (Mashile, 2025). The unavailability of quality information, reduced investments, and technology are also defining features of PE and VC markets in South Africa (SAVCA, 2025). By implementing AI-based tools, the companies would be able to tackle these challenges by making the data more accurate, evaluating the flow of deals more effectively, and diversifying their portfolio more efficiently. As such, the commercial need of the current research is to explain how AI would facilitate the decision-making process of selecting deals, become more efficient, and compete in the evolving market in South Africa.

1.3.2 Theoretical Need

Theoretically, there is still a considerable gap in the knowledge on the effect of AI adoption on human decision-making within the PE/VC framework. Although the literature on AI usage in financial markets is expanding, much research is being done concerning developed economies or their use in public markets (Sanchez, 2020). There is a paucity of studies regarding the interaction between AI and human cognition (i.e., heuristics, trust, and intuition) in the decision-making process within PE/VC firms (Csaszar et al., 2024). This study has helped advance the theory by addressing the interplay between AI adoption, decision theory, and behavioural finance.

The information processing theory presents a practical perspective by examining how organisations obtain, perceive, and exploit information in unpredictable settings (Bai & Zhao, 2021). The information processing theory is more practical in that it studies the way organisations acquire, receive, and use information under uncertain environments

(Bai and Zhao, 2021). Equally, the principal-agent theory gives an indication of how AI may be used to reduce the informational asymmetry and increase the accountability of investors and fund managers (Ferrati and Muffatto, 2021). The research makes its contribution to scientific knowledge and understanding of the influence of AI on decision-making in situations with uncertainty by implementing theoretical frameworks to the PE /VC investment scenario. It further adds to the literature by highlighting how institutional, infrastructural and cultural considerations play their roles in the adoption of AI in new markets, broadening the debate on AI-based decision-making across the globe.

1.4 Research Aim and Objectives

Aim:

To explore how artificial intelligence (AI) influences decision-making in deal selection within private equity operating in South Africa, and to identify factors affecting its adoption, trust, and effectiveness.

Research objectives

The primary objective of this study is to examine how AI-enabled decision-support tools influence the deal-selection process within private equity (PE) and venture capital (VC) firms by practitioners in South Africa.

To achieve this aim, the study pursues the following specific objectives:

- To explore how AI technologies are currently utilised by PE and VC practitioners during the deal-selection phase in South Africa.
- To assess the perceived impact of AI tools on the quality, speed, and consistency of investment decision-making.
- To identify organisational, technological, and human factors influencing the adoption and trust of AI in PE and VC decision-making processes.
- To evaluate the interaction between human judgment and AI-based insights in shaping final investment decisions.
- To develop recommendations for enhancing AI integration and adoption within South Africa's private capital ecosystem.

1.5 Scope of the Research

This research is based on the deal-selection stage of the work of the South African private equity (PE) and venture capital (VC) firms, in which, to date, investment decisions are made primarily by humans despite the increasing use of artificial

intelligence (AI)-based solutions (SAVCA, 2025). The study also does not consider the post-investment processes, including portfolio management, value creation and exit strategies to ensure a proper focus on the initial screening and assessment of deals (Block et al., 2019). The focus audience will be the decision-makers, including partners, analysts, and investment managers, who are directly interested in evaluating and picking investment opportunities (Ross et al., 2021).

The qualitative research design is used, and semi-structured interviews are applied to obtain in-depth information about how PE/VC professionals perceive AI technologies in decision-making and integrate them into their decision-making process (Creswell & Poth, 2018). This method would allow studying both the technical and behavioural dimensions, such as the trust in AI systems and organisational preparedness to go digital (Kearney, 2024). Although the sample size is restricted in generalisation to other markets as it focuses on South African firms, it helps to gain a significant contextual insight into AI adoption within emerging markets, where digital infrastructure and knowledge are still in their developmental stages (Deloitte, 2023; Mashile, 2025). The study is also limited to firms with a certain Degree of digital capacity, as non-digital firms are not considered to be within the technological spectrum of AI implementation (World Economic Forum, 2025).

Chapter 2: Literature Review

2.1 Introduction

In this chapter, the author conducts a literature review of the influence of Artificial Intelligence (AI) on decision-making in the selection of deals in the context of the work of the private equity (PE) and venture capital (VC) practitioners. It discusses the way AI technologies have reinvented the old methods of investing through the improvement of data analysis, predictability and decision efficiency. The chapter starts with the definition of the main concepts of AI and investment decision-making, and then continues with the discussion of the traditional PE/VC decision models and their shortcomings. It next examines the development of AI-based tools in various phases of deal selection and the changing interaction between human judgment and algorithmic systems. Appropriate theoretical frameworks that underpin these dynamics are also addressed. Lastly, the chapter reveals the gaps in existing literature, especially the adoption and behavioural components of AI in South Africa of the private equity space.

2.2 Conceptualising Artificial Intelligence and Decision-Making

2.2.1 Defining Artificial Intelligence (AI)

Artificial Intelligence (AI) has now developed into a theoretical framework and a technological paradigm transformer as it changes the way organizations create, process, and utilize information in strategic decision-making (Radanliev, 2024). In general, AI may be described as the attempts to replicate the human mental activities, including reasoning, learning, and problem-resolving, with the help of computational systems. Krishna (2024) believe that AI will be able to overcome the constraints of human thinking because it can be scaled and be precise in multidimensional and data-heavy processes.

As an example, machine learning algorithms can handle millions of data points to identify patterns and correlations which would be difficult to identify by human analysts (Sarker, 2021). In the case of the private equity (PE) and the venture capital (VC), these capabilities play a critical role in identifying investment opportunities during the early stages, maximizing due diligence, and predicting the outcomes of the exit (Cumming et al., 2022).

Das et al. (2023) state that AI systems are as objective as their input data is. The algorithmic models that are trained using skewed datasets in the past might continue to support or even increase the existing disparities, especially when it comes to financial

decisions. Therefore, albeit AI brings about analytical rigor and speed, its reliability in epistemics depends on human supervision, transparency, and readability. The question that is highly controversial however is not whether AI should be incorporated into decision-making but rather how it ought to be created and regulated to strike a balance between the computational efficiency and ethical and contextual integrity.

2.2.2 Decision-Making in Private Equity and Venture Capital

In PE and VC to make decisions, the options to be chosen, analysed, and controlled are to be made in the presence of uncertainty, incomplete information, and time constraints. Conventional models in these areas are concerned with such financial indicators as internal rate of return (IRR), market potential, scalability, and management ability (Ridwan et al., 2025). Even the traditional investment decision-making model in private equity (PE) and venture capital (VC) advocates believe that intuition is a crucial element that leads to the identification of good venture opportunities because it is based on experience and pattern recognition. This has been in line with the concept of expert intuition proposed by Okoli & Hatami-Marbini (2021) which is the ability of experienced decision-makers to make quick and precise decisions after years of exposure to systematic settings.

Conversely, empirical studies are beginning to demonstrate the cognitive malfunctions in human decisions. The Prospect Theory by Kahneman and Tversky reveals that loss aversion, overconfidence, and confirmation bias are very likely to occur to investors (Singh et al., 2024b). Such distortions of the mind may result in poor investment decisions or herding, whereby capital is channeled in areas or fields it recognizes. The mitigation of such biases can be possible through AI-based analytics, which bases evaluation on a factual and objective basis. According to Nishant et al. (2023), substituting human heuristics with transparent algorithms might easily cause a direct replacement of bias with another behaviour: algorithmic bias due to bad or incomplete data.

2.3 Traditional Investment Decision-Making in PE/VC

2.3.1 Classic Models and Criteria

PE and VC classic decision-making models are originated in financial economics and behavioural management theories. The framework by Kaplan and Stromberger revolves investment decisions on the three aspects, which are market potential, product differentiation and quality of management (Seyed Parsa Parvasi et al., 2024). This

model emphasizes the use of due diligence in the determination of the tangible and intangible value drivers. The entrepreneurial characteristics that used when determining the investment attractiveness were also leadership and innovation.

Those classical models such as Modern Portfolio Theory, the Capital Asset Pricing Model, and Expected Utility Theory (von Neumann & Morgenstern are based on a rational actor who systematically processes information in order to obtain expected returns maximization. Researchers like Hanlon et al. (2021) believe that such an organised model has been successful in mature markets where the information asymmetry is moderate. A combination of financial modelling, market intelligence, and professional panels has in the past offered a secure foundation of making decisions on deals and risk management.

Nevertheless, behavioural economists dispute the rationalist assumption, said to be constrained by cognitive boundaries and complexity of the environment. As a matter of fact, PE/VC professionals are exposed to ambiguous data, speedy changes in the market, and developing technology that does not allow purely rational analysis. Big data has introduced information overload and it is more difficult to identify meaningful patterns in isolation with the human eye.

2.3.2 Limitations and Biases

Although traditional investment decision processes in the sphere of the private equity and venture capital have been long-established, they continue to be biased, subjective, and inefficient (Gabay, 2025). Ekström & Swärd (2024) have recorded gender and racial prejudices in venture capital, and they discover that female-led companies are consistently undervalued relative to male-led ones even with similar performance factors.

Methodologically, most analysts use static financial model like discounted cash flow (DCF) or net present value (NPV). The tools are criticized by Weil, (2023) who says that they cannot explain the non-linear nature of the markets which are dynamic. The models are based on the assumptions of market stability and predictability- assumptions, which can hardly be made in new or technology-driven industries. Advocates of AI-based analytics refute that algorithmic decision-making can be used to overcome these inadequacies. According to Minou Rabiei et al. (2025) algorithms can detect hidden trends and new opportunities unnoticed by human analysts thanks to the use of continuous learning and real-time data processing. As an example, NLP algorithms can be used to analyse sentiment in the media or in social data to indicate a change in consumer perception before it is reflected in financial indicators.

Nevertheless, critics remind that AI will not be able to get rid of bias; on the contrary, it will be able to encode and amplify it. Augusto (2022) posits that algorithms are views integrated into the code, i.e., their predictive capabilities are related to the suppositions and priorities of the creators. In addition, AI systems do not have a lot of contextual awareness. They might not comprehend motivation of founders, moral aspects, and cultural peculiarities, which can contribute, to investment success. Thus, instead of giving up on AI, companies need to shape its usage to powerful governance, transparency, and human control frameworks. Using algorithmic accuracy and human judgement of the situation, venture capital and private equity firms can use AI analytics whilst reducing its ethical and cognitive blindness.

2.4 Emergence of AI in Private Equity Decision-Making

2.4.1 The Rise of Data-Driven Investing

The speed at which artificial intelligence has been applied to the industry of private equity and venture capital has moved the process of selecting the deals to be more data-driven and less intuitively based (Adewale, 2024). Historically, the investment community was inclined towards qualitative judgments and contacts. Algorithms that promote artificial intelligence are necessary today as the information volume grows exponentially, and the computational power increases.

Advocates believe that data-driven investing lowers the human factor and cognitive constraints. Pagliaro (2025) observe that AI capabilities to handle multidimensional and complex data allows investors to identify the hidden market correlations that cannot be identified by human analytical tools. These tools shift investors away to retributory analysis, to predictive analysis, establishing a competitive edge in competitive markets. As an example, AI-based sentiment analysis can identify the earliest signs of innovation trends or consumer perception changes so that firms can take the opportunity before it becomes a household name (Taherdoost & Madanchian, 2023).

Nevertheless, this change does not pass without criticism as Desai et al. (2022) note that data-driven frameworks may produce a false sense of objectivity, and that algorithmic decision-making is viewed as an intrinsically better approach than human decision-making. The AI systems are based on previous data that can introduce inequities and systemic biases of the past. In private equity and venture capital, when datasets are typically incomplete or unrepresentative, such as in emerging markets such as South Africa, this may result in skewed predictions that support exclusionary investment patterns.

2.4.2 AI-Enabled Tools in Deal Screening

The initial decision in investment decisions is deal screening as AI has changed this stage. Previously, sourcing transactions involved a lot of networking and manual evaluation of bids. That was a time-consuming process, confined within the personal sphere, and prone to individual biases (Jayanth & Rajendran, 2024). Most of this is done automatically nowadays with AI-powered screening technologies. They filter and rank investment prospects with the help of natural language processing (NLP), machine learning (ML), and predictive scoring systems.

Contemporary AI applications like Affinity, Crunchbase Pro, and Pitchbook Intelligence scan through thousands of data points, including financial metrics, signs of online engagement, and others, to identify potentially successful startups (Chen, 2025). As Rasivisuth (2025) demonstrate, the success of venture forecasting can be done by training the ML algorithms on the historical success data to identify the ones that might exit successfully or develop sustainably.

Nevertheless, these instruments are also dangerous, as they may strengthen homogeneity in investment portfolios, whereas they enhance efficiency and scalability. As observed by Hu et al. (2022)., algorithm-based screening is more likely to prefer the ventures that are similar to the ones that are already successful, which supports path dependence. When male-led or Silicon Valley-based successes have been the case in the past, there is a likelihood that the algorithm will focus on and give preference to the same profile automatically (Bajarin, 2024). The black box issue can also exist in AI models and render them not very transparent, which means that a high ranking is difficult to comprehend and dangerous to question by investors. This obscurity undermines accountability and may destroy confidence in investment committees.

2.4.3 AI in Due Diligence and Risk Assessment

AI is crucial to due diligence and risk assessment, historically, due diligence was done manually by examining financial documents, legal documents and background information on the management of the business, which was subject to errors (Käyhkö, 2025). To a great extent, AI automates this work through sophisticated data analytics and allows investors to process a great deal of information in real time. NLP can learn insights in unstructured text like contracts or news coverage, regulatory filings, and identify red flags early.

Empirical data such as the case by Nor et al. (2022) demonstrates that AI-based risk models are superior in detecting anomalies as well as forecasting a probability of failure compared to conventional methods. AI offers a more comprehensive view of the risk of

investing as it considers numerous sources of data, i.e., macroeconomic trends, market sentiment, operational metrics, etc. These technologies are also utilised to support ESG assessment, which coordinates due diligence to the sustainable investing agenda of financial globalised (Asif et al., 2023).

Nevertheless, interpretability and richness of context are still feared. Algorithms are able to find relationships and not identify causality, and in this regard can be subject to over fitting or false positives (Ainura Tursunalieva et al., 2024). In complex settings, such as emerging economies, lack of data, non-congruity and regulatory non-transparency may further undermine the model predictability. The opponents believe that human judgment is needed when interpreting context-dependent risk including political instability, culture, or ethical scandals, which AI would not be able to measures (John-Mathews, 2022). There are also ethical concerns regarding the utilisation of personal or proprietary data to conduct due diligence, which creates privacy and data security concerns.

2.4.4 Predictive Analytics and Performance Forecasting

The use of AI in predictive analytics and forecasting performance has changed the way investors expect portfolio companies to perform. Predictive models leverage the machine learning to assess the success factors such as market scalability, funding velocity, and team dynamics, to create probabilistic financial forecasts. According to Kumari (2024), the models assist investors in shifting their portfolio optimisation towards being reactive than proactive. Indicatively, AI can also identify the underperforming investments at an early stage, recommend remedial measures, and anticipate the best time to exit to increase returns and reduce losses.

According to its enthusiasts, predictive analytics democratise the decision-making process by substituting intuition with measurable information, enhancing transparency and accountability (Bronfman, 2025). Machine learning has the potential to integrate both the macroeconomic factors and the customer acquisition measures alongside the innovation measurement into the complete risk-adjusted predictions. The platform BlackRock Aladdin depicts the capability of AI-powered forecasting to unite several data streams to inform dynamic investment decisions (BlackRock, 2024).

Nonetheless, there is scepticism, by the opponents, regarding the predictive model in uncertain non-stationary markets in terms of epistemology. Social, political, and behavioural factors are financial environments, difficult to model using fixed datasets. Ross et al. (2021) claim that machine learning can be successful when its success is governed by historical consistency, but disruptive innovations can overcome trends

(Faculty of Public Health, 2017). The problem of over fitting still exists: the models can work well on training data but fail in the context of the actual volatility.

2.5 The Interplay between Human Judgment and AI

2.5.1 Complementarity Rather Than Replacement

Recent research refocused AI in decision-making as complementary but not an all-over substitute to human judgment. Hemmer (2024) established a theoretical framework that explains how human-AI complementarity can be developed based on representation, computation, and control. It was demonstrated that task division (AI-scaling and pattern recognition) paired with human concern (novelty and context) is the most efficient. It also stipulates situations in which complementarity does not work out, and provides normative information on how to design effective collaboration. Nonetheless, empirical syntheses made optimism challenging; a meta-analysis by Vaccaro et al. (2024) observed that human-AI teams tend to do worse than the best solo agent in decision tasks, creating net losses on most decision problems and gains on creative tasks, suggesting that complementarity is weak and task-specific.

Concerning Venture Capital-based research, Cao et al. (2024) composed and evaluated a data-driven, transformer-based method of sourcing investment targets of VC/PE, based on firm time-series and alternative signals to forecast the probability of success (TMTSC approach). It showed that algorithmic screening can significantly boost throughput and hit rates at early stages in comparison to simple heuristics, and it exhibited obvious operational benefits at the triage/screening phase, where patterns and scale are important. Nevertheless, the study was clear that the model outputs need human filtering to provide contextual fit and founder assessment. Therefore, it depicted AI as an accurate filter instead of a solitary decision-maker. In contrast to the predictive-model work by Lyonnet and Stern (2024), which demonstrates that VCs occasionally forgo predictably good firms and invest in predictably poor ones. The study emphasised technical possibility (VCs improved predictive tools) and concentrates on organisational choice (VCs do not always take predictive information). The discussion highlights that, although AI is effective in improving efficiency in deal selection, its worth is determined by the balance between human expertise and algorithmic understanding, which is also complicated by the behavioural and cognitive dynamics that are discussed further.

2.5.2 Behavioral and Cognitive Aspects

Behavioural literature found two interactive risks of human working with AI, including aversion to algorithms (under-reliance after observed errors) and automation bias (over-

reliance despite warning signs). The experimental analysis by Filiz et al. (2023) demonstrated that the aversion increases with the severity of decision consequences, suggesting the possibility of investors refusing AI at the very time when it could benefit the majority. Recent studies in the context of investment-decision and strategic-decision emphasised the importance of cognitive and behavioural dynamics in defining the interface between human beings and AI tools. As an illustration, research by Csaszar et al. (2024) demonstrated that large language models can also outcompete human strategists when it comes to creating and assessing business plans, but human decision-makers are still sceptical and overrule AI recommendations, which reflects a powerful effect of trust, control, and perceived human competence. Likewise, Montanaro et al. (2024) conducted an analysis of patterns of VC financing and discovered that AI ventures are less financed than non-AI ones, and human investors might discount AI-related opportunities by perceiving greater uncertainty or limited cognitive comfort related to AI. These studies attributed their findings to human judgmental biases (aversion, heuristic override) as opposed to functional algorithmic impairments. Such behavioural patterns show that even sophisticated AI-based systems are affected by human perceptual and trust problems, and it is necessary to explore further how cognitive biases influence and possibly mislead AI-aided decision-making in investment procedures.

2.5.3 Cognitive Biases and AI Mitigation

Recent researchers on AI and bias reduction in venture capital were discovered to be both optimistic and wary. Houser and Kisska-Schulze (2022) argued that algorithmic tools could break through the existing VC biases, like gender and pattern bias, through coercive consistency of data. Nevertheless, they cautioned that when biased human data is used in training AI, automation could only enhance inequity with effectiveness. Furthermore, this debate was empirically extended by Balan et al. (2025), with evidence that AI-guided screening models within VC minimised cases of confirmation bias, where investors used fewer previous stereotypes about the founding person. Nevertheless, it also brought about the automation bias in which decision-makers blindly trusted excessively to the model outputs. Conversely, Nerella (2025) reported the presence of confirmation, recency, and algorithmic biases in AI-based portfolio management and suggested explainable AI (XAI), bias testing, and human-in-the-loop systems as the main mitigation strategies. Nerella's analysis was, however, very conceptual and does not empirically test these interventions in live VC situations. Collectively, these works indicated that AI has the capability to reveal and regulate human heuristics but cannot

unilaterally ensure rationality. All research pointed out a dissimilar failure mode - data bias in Houser and Kisska-Schulze data, trust imbalance in Nerella, and automation drift in Balan et al. research- suggesting that successful mitigation may rely on feedback design and human-AI calibration. Therefore, even though AI provides the means of minimising bias, it also generates novel forms of algorithmic reliance, which pose a question as to whether the organisational design and feedback systems can support the balanced human-AI cooperation, as the cultural attitudes can also influence this dynamic.

2.5.5 Cultural Resistance to AI Adoption

Recent empirical studies indicate that cultural resistance, rather than technical constraint, is the principal constraint to AI adoption in investment firms. The qualitative study of European VCs by Väyrynen (2025) is based on the fourteen semi-structured interviews that reveal that practitioners are comfortable with AI in the areas of sourcing and data management but are reluctant about automating the process of assessing founders and making final IC decisions due to issues regarding identity, trust, and reputation (Väyrynen, 2025). These barriers are supported in a mixed-methods analysis by Rydstrand and Reichard (2025) across asset managers (including VC practitioners): explainability, regulatory uncertainty, and a perception of loss of control are significantly predictive of limited adoption, and respondents indicate use of AI predominantly to administer roles rather than to make decisions. To supplement these, Kellogg et al. (2020) show through the ethnographic analysis that cultural resistance is due to threatened expertise and the changing power relations between professionals and the AI, which is seen as surveillance, rather than as an enhancement. The three studies bring together the same diagnosis, which is trust, explainability, and identity protection, but they vary in terms of their scope and approach. Therefore, the cultural and institutional resistance is still a characteristic obstacle to the successful implementation of AI, which indicates the necessity to study the manner in which local settings, including the investment climate in South Africa, mediate these international processes and adoption trends.

2.6 Global vs. South African Context

The adoption of AI in PE/VC across the world has increased, though the literature highlights the significance of heterogeneity in terms of intent, capacity, and influence. Empirical surveys and firm-level research show that screening and deal-sourcing automation are the first and most widespread used, and that size and speed of screened

opportunities are measurably improved, but long-run performance improvement has uncertain evidence. To illustrate, a recent empirical study of the operations of European VC by Ronco and Barontini (2025) captures the fact that adopters report significant decreases in due diligence time and increased progress in the screening throughput. Nevertheless, they warn that evidence of long-lasting alpha provided by AI adoption has not been extended, and it depends on complementary skills and data. Quantitative study of worldwide VC investments (US, UK, European, Chinese, and Australian) by Montanaro et al. (2024) is complementary to this as it reveals the fact that AI-focused deals are not similar to other tech investments (varying sector mixes, valuation dynamics, and investor profiles). It means that AI is not only an object of investment but is also a working input, a twofold nature that makes it difficult to make causal statements about the impact of AI on fund performance.

Conversely, opportunity and structural friction are evident in the South African context and the African context overall. According to market reports, there is an increasing proportion of AI-oriented VC deals in Africa (AI being among the accelerating subsectors), which points to the dynamism of entrepreneurship and interest of the investors (AVCA, 2024; CIPIT, 2025). At the same time, these reports also highlight shallow data ecosystems, disjointed regulatory frameworks, and a lack of funding to support advanced AI implementation within PE/VC firms themselves (as opposed to investing in AI Startups). The three main differences identified by the policy analyses of African markets include weaker data infrastructure and interoperability, which lower the viability of predictive models that make use of rich historical signals (1); talent scarcity and increased costs in hiring/retaining data scientists within funds (2); regulatory and institutional uncertainty that exacerbates risk aversion among GPs and LPs (AVCA, 2024; CIPIT, 2025). These limitations imply that African PE/VC tend to believe in AI more as a portfolio play (investment in AI Startups) over AI as a core part of internal deal-selection.

These situational constraints highlight why it is necessary to study the way South African investment professionals are starting to implement AI applications in their own institutional and market conditions, balancing global practices against local conditions. According to Regina et al. (2024), South Africa is one of the most active health-tech centres in Africa, which uses AI and big data in the decision-making of venture capital. Even with good healthcare infrastructure, access and affordability issues continue to be a challenge. Machine learning and geospatial analytics are becoming a favourite tool of investors when analysing Startups to improve decision-making and predict performance

to achieve better investment results. In general, global markets indicate that AI has matured and diversified in PE/VC, but South Africa is still in the emergent stage of the process, which is selective experimentation, sectorial concentration, and a slow transition to a state of embedding AI in core investment decisions as local data ecosystems and institutional preparedness develop.

2.7 Theoretical Frameworks

Integrating AI in PE and VC decision-making can be critically viewed through various theoretical perspectives explaining how information asymmetries, thinking and behavioral biases affect investment decisions. Principal-agent Theory, Information Processing Theory (IPT) and Behavioral Decision Theory (BDT) are the three most applicable frameworks in the present situation. The three of them offer a unique but complementary insight into the way AI changes classic decision dynamics and creates novel governance and ethical challenges.

The principal-Agency Theory (Jensen and Meckling, is a classical theory that is used to explain the agency problems between the investors (principals) and fund managers (agents) where the latter could act in their own interest because of information asymmetry. This is reflected in PE/VC as the fund managers favour deals that lead to the short-term performance or reputation instead of the long-term value. In this regard, AI has been suggested as a neutral process that increases transparency, reduces moral hazard, and gives an overview of data (Economist, 2023). However, the important issue is that even algorithms could emerge as new actors, acting as a part of a black box that the investors themselves might be not fully aware of. The agency risk can be redefined by shifting away to algorithmic bias (Augusto, 2022), which implies that it does not disappear but is rather transformed to opaque machine self-interest. Therefore, AI does not solve the agency problem, but it changes its nature, in need of new accountability tools, including explainable AI and algorithmic auditing.

The Information Processing Theory sees the organisations as information systems that have to obtain, interpret, and utilise information effectively in order to make quality decisions. In this regard, AI expands the cognitive ability of the firm by analysing large volumes of data, developing trends, and predicting performance-related results in a level that is unable to be performed by humans (Balan et al., 2025). Critics like Santos & Papa (2022) however claim that the computational efficiency will result in overfitting of data, with models giving more importance to data regularities and less importance to context. The PE/VC investment choices are often based on abstract qualitative variables like the drive of its founder or culture fit, which AI might not capture.

2.8 Conceptual Model

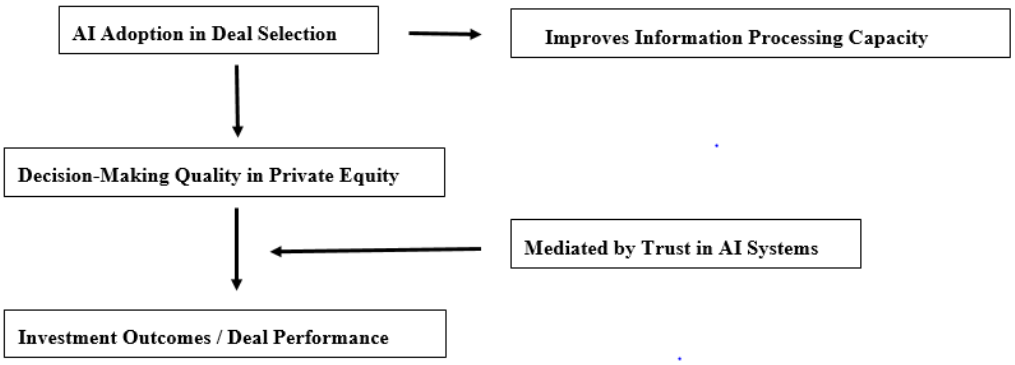

Figure 1: Conceptual Framework

The conceptual framework (Fig 1) of this study merges Principal-Agent Theory and Information Processing Theory (IPT) to conceptualise the effect of AI adoption on the process of decision-making in South African PE/VC firms. AI can be viewed through the Principal -Agency Theory as a tool of minimising information asymmetry and agency cost between the investors and the fund managers. Complementarily, IPT conceptualises AI as a bolster of information processing of firms in the face of uncertainty. The combination of these theories implies that AI tools can be used to enhance the quality of decisions through additional transparency and predictability, mediated by trust in artificial intelligence tools, and with eventual ramifications on investment performance and deal results under the contextual institutional regulation.

2.9 Research Gap

Although the research on the adoption of AI in PE/VC grew worldwide, there exists a significant gap in terms of its implementation into the South African setting, where the structural, institutional, and cultural factors are quite different. Predictive models, human-AI complement, or bias-reduction in mature markets have taken centre stage (Hemmer, 2024; Vaccaro et al., 2024; Cao et al., 2024), yet little is available on how investment professionals interact with AI along end-to-end deal-selection processes in South Africa. The literature has emphasised human-AI trust, algorithm aversion, and cognitive biases

(Filiz et al., 2023; Csaszar et al., 2024; Montanaro et al., 2024), but little focus has been on the interaction between humans and AI in high-stakes, collective decision-making (investment committees) in developing nations, particularly South Africa. In addition, cultural resistance, the lack of infrastructure, and the shortage of talent limit the use of AI (AVCA, 2024; CIPIT, 2025; Väyrynen, 2025), but the role of cultural issues, incompatibility, and predictive potential is not studied in the context of South Africa. This study fulfilled these gaps by examining how South African VC/PE practitioners discover, embrace, and incorporate AI tools, balancing the insights of algorithms with human judgment to add value to deals.

2.9 Summary

This chapter presented a critical examination of current literature about AI adoption in PE/VC decision-making. The chapter highlighted theoretical, behavioural, and contextual dimensions shaping interaction between humans and AI. It was revealed that although AI enhances the processing of information and efficiency in decision-making, there are moderating agents such as trust, cultural resistance, and institutional capacity, particular in emerging markets like South Africa. These identified gaps in empirical understanding and contextual application lay the foundation for the next chapter, wherein the formulated study's research questions are justified in light of existing literary work.

Chapter 3: Research Questions

3.1 Introduction

In this chapter, the research questions underpinning this study are presented. The application of artificial intelligence (AI) in the decision-making of South African-based private equity (PE) and venture capital (VC) is at its infancy, as the literature review showed. Although AI has proven to be a promising technology in automating the processes of data-driven investments in developed markets and was adopted by management as a method of automating resource allocation, there has not been any empirical evidence to investigate how it can assist human judgment, influence trust, or improve the level of decision-making in PE/VC firms of developing economies.

Since there is little theoretical and empirical evidence, this study takes an exploratory approach, led by research questions rather than testable hypotheses. All the questions are guided by the gaps in the literature and in accordance with the study's objective and aim.

Research Questions

Primary

RQ1: How do investment professionals in South African venture capital (VC) and private equity (PE) firms identify and engage with artificial intelligence in decision-making and deal selection?

This key question explores the essence and extent of interaction between AI technology and human decision-making processes in PE and VC situations. Earlier research indicates that although AI will enhance the objectivity and efficiency of investment analysis, it questions conventional heuristics and intuitive decision-making (Huang & Rust, 2021; Gompers et al., 2020). The process of practitioners in a new economy comprehending and engaging with these tools provides crucial perspectives on how the decision ecosystem is progressing in new economies (Brynjulfsson & McAfee, 2017).

Secondary

RQ1: What influences adoption or even resistance to AI tools in PE/VC?

Implementation of AI in investment companies has a tendency of being predetermined by technological and human factors. According to Technology Acceptance Model (TAM), ease of use and perceived usefulness are significant variables that determine acceptance (Davis, 1989). The other factors that determine the adoption of AI in investment are organisational preparedness, attitudes of leadership, and perceived risk

(Ransbotham et al., 2018). Researching these determinants in the PE/VC context of South Africa, it is possible to see how the forces related to the local environment may affect the technological diffusion (Paschen et al., 2020).

RQ2: How does the infrastructure shape AI integration in terms of institutional and cultural context?

According to institutional theory, innovation adoption is significantly affected by national infrastructure, regulatory systems, and cultural attitudes toward technology (Scott, 2014). The combination of developed financial systems and socio-economic inequalities is also a perfect example of South Africa, and it is worth analysing how the specified conditions facilitate or limit the introduction of AI (Kshetri, 2021). This question thereby explores the macro-level setups such as technological infrastructure, data availability and institutional assistance that influence the use of AI in investment practice.

RQ3: Can AI tools replace or support judgment in the deal cycle process?

Whether AI complements or substitutes human judgment in investment-making is being debated (Agrawal, Gans, and Goldfarb, 2018). Algorithms will be more useful in data analysis, but human knowledge will be essential to explain the qualitative features of entrepreneurial potential and the market (Gompers et al., 2020). The question investigates the place of AI tools in the deal cycle regarding deal sourcing and evaluation. It evaluates whether professionals view them as partners or rivals in the cognitive decision-making processes.

RQ4: How does transparency, control and predictive capability affect AI acceptance?

The perceived trust in AI systems is closely linked to perceptions of transparency, interpretability, and control (Doshi-Velez & Kim, 2017; Rai, 2020). Professionals tend to be wary of delegating decision-making to opaque algorithms in PE/VC situations, especially when making high-stakes decisions. This question investigates the role of explainability and control tools in explaining the acceptance of AI, and whether predictive accuracy can counteract transparency and autonomy concerns.

Chapter 4: Research Methodology

4.1 Introduction

This chapter has introduced the methodology of research in which the research goals and objectives were to be actualised. It established the broad methodology with which the role of artificial intelligence in decision-making in deal selection was determined in the South African based private equity firms. The research design that was presented and discussed in the chapter informed the study. It also described how the data would be collected and analysed, the target population, sampling technique and the data collection technique and the data analysis process. The section revealed how the methods adopted were appropriate to support the research goals and guarantee validity and reliability. Moreover, it paid attention to the measures to promote ethical practises and quality of data. The chapter ended with the details of the limitations and delimitations of the research, which contributed to determining the scope and the boundaries of the study. On the whole, the chapter has clearly and well-structured detailed the study design and methodology.

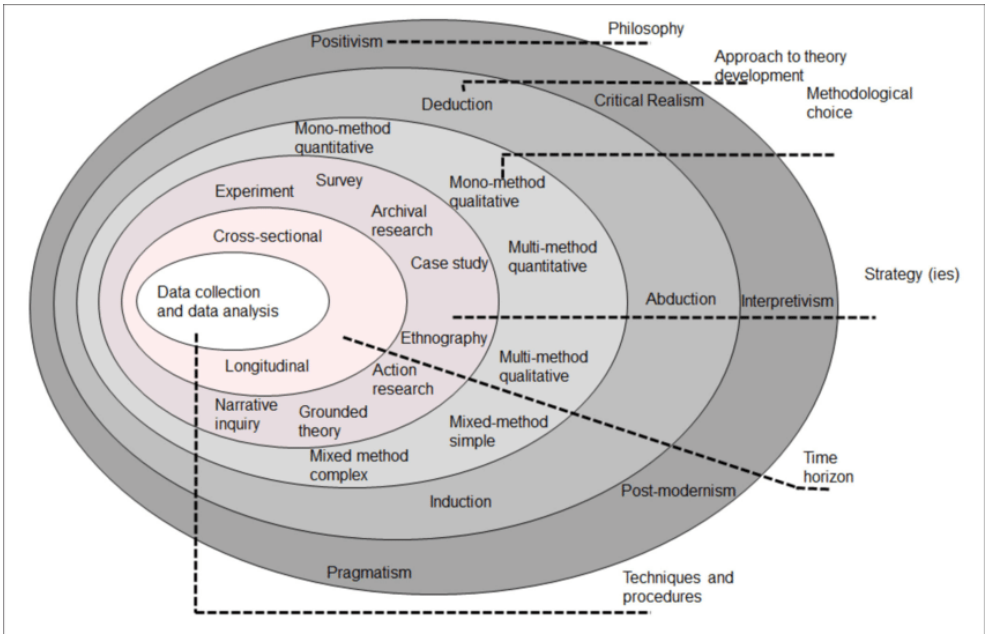

Figure 2: This depicts the Saunder's onion layers. Source (Saunders et al., 2019)

4.2 Purpose of Research Design

The research design was used as a guideline that guided all the processes in this research. It provided a logical system of collecting, evaluating and analysing data to answer the research questions (Antony et al., 2020). The primary goal of the design was to study the effect of artificial intelligence (AI) on the investment decision-making process in the domain of private equity firms. The qualitative exploratory design was

selected as it created the opportunity to comprehend the experiences and perceptions of professionals using or hesitant to use AI tools in the process of deal selection.

Quantitative design was also to be taken into account, but it could not be chosen as the subject matter involved interpretation of subjective human judgments, not the statistical relationships (Mohajan, 2020). In South Africa, where use of private equity AI is still in its infancy, there was limited data that could be measured. Thus, an exploration design contributed to the discovery of patterns, attitudes, and issues, which could not be revealed numerically. The design further permitted the new theme and theoretical understanding to rise out of actual experiences and assist in the creation of knowledge in a field where there is not much local research. All in all, the selected design was flexible, contextually relevant, and in-depth, which was necessary to address the objectives of the study.

4.3 Research Philosophy

This study was guided by the interpretivist philosophy, which attempts to explain human experiences and explain social phenomena using the meaning that people attach to them. Interpretivism was the appropriate methodology since the study was intended to understand the perception and use of artificial intelligence (AI) by investment professionals in decision-making processes. It allowed the researcher to describe the views of the participants in terms of their opinions and experiences as opposed to basing the frames on the observable facts or quantitative data (Antony et al., 2020; Mohajan, 2020).

Interpretivism was more favourable to positivism because, in positivism, the criteria are objective measurement, generalisation, and hypothesis testing, which cannot be applied to subjective human reasoning and perception. However, it opposed pragmatism, which emphasises practical results more than interpretive richness. Since private equity decisions are both a mixture of human judgement and technological understanding, interpretivism presents itself as suitable to examine such intricate interactions (Pervin & Mokhtar, 2022). This philosophical position advocated more profound discussion of trust, bias, and professional judgement with regard to adopting AI tools. It promoted open-ended questioning, which enabled the researcher to decipher hidden meanings and comprehend how the participants incorporated technology within their professional and cultural environments. Therefore, interpretivism offered an excellent basis in exploring the human-technological aspects of investment decision-making.

4.4 Research Approach

The research design in this study was an inductive research approach, where theory was developed based on data instead of testing existing theory (Gehman et al., 2018). The objective was to learn the influence of artificial intelligence (AI) on investment decisions by the decision-making by practitioners of a private equity firm. Professionals were interviewed to provide the data, which was subsequently organised, coded and clustered by themes. These themes allowed the researcher to establish the pattern and relationships that characterised how AI tools were perceived, adopted, or rejected in deal selection. Inductive was the best method because there had been few prior researches on AI-based decision-making within South Africa in the private equity market. This method was employed to allow the emerging of new ideas directly out of these experiences, rather than commencing with a predetermined theory. On the other hand, the deductive approach would have required a hypothesis based on models, which is inappropriate because the study at hand is an exploration (Casula et al., 2020). Induction also ensured flexibility and transparency in the data collection process, which enabled the researcher to change in accordance with the insights that naturally appeared (Gehman et al., 2018). The approach encouraged a bottom-up approach to versatile social and technological interactions, and therefore is most applicable to the exploration of novel or under-researched problems. Overall, the inductive approach enabled the realisation of context-dependent knowledge and theory founded on practical experiences.

4.5 Methodological Choice

The study employed a mono-method qualitative design where qualitative data were collected and analysed. This choice aligned with interpretivist philosophy and inductive method, which puts more emphasis on understanding human experience and meaning (Saunders & Darabi, 2024). The use of one qualitative method helped the researcher explore the logic, emotion, and sense of the participants. Qualitative design was appropriate because it was aimed at describing and comprehending complex decision making processes, and not quantifying them. On the other hand, quantitative research is based on the variables that can be measured and analysed in numbers, which would not have brought the richness of the experiences of the participants using AI tools. Similarly, a mixed-method design was avoided to maintain integrity and not to bleach the richness of interpretation (Ahmad et al., 2019). The qualitative interviews provided detailed accounts of the effects of AI on the deal selection, trust, and professional judgement (Saunders & Darabi, 2024). These observations helped in the enhancement of a

superior perception of attitudes and behaviours that would not have been detected when using numbers alone. The method of mono-method therefore gave focus, both in-depth and uniformity between the research questions and the overall design of the study.

4.6 Research Strategy

The research strategy chosen to implement in the present study was the semi-structured interviews. The chosen method was reasonable since it allowed the researcher to investigate the complex decision-making procedures, which were linked to human cognition and the use of artificial intelligence (AI). Interviews were not highly regulated and allowed to ask follow-up questions in case it was needed to make the participants elaborate the experiences, problems, and perceptions in their own words (Heath et al., 2018). To make sure that all the steps of the decision-making process will be covered, the questions asked during the interview were formulated in the terms of the main stages of the deal selection, sourcing, screening, due diligence and the examination of the investment committee. This plan helped to unveil the influence of AI tools on these processes and how the professionals are caught in the middle between the information that these machines presented and individual opinion. Other strategies not selected included surveys or ethnography. Professional reasoning was so deep that it could not be included in surveys, and ethnography was not suitable due to the secrecy in investment environments (Heath et al., 2018). Semi-structured interviews, therefore, offered the most appropriate means of identifying both the behavioural and technological elements of AI use in the realm of private equity.

4.7 Time Horizon

This study utilised a cross-sectional time horizon. The collection of data lasted three months, which enabled the researcher to achieve the up-to-date experiences and perceptions of the participants towards AI in decision-making. This design allowed a picture of the usage of AI tools at a certain moment in time by the private equity firms. The longitudinal design that follows changes with time was not adopted since the study was aimed at exploring current practises and not tracking the further progress (Audulv et al., 2022). The cross sectional study fitted the exploratory nature of the study, as the study concentrated on the instant insights as opposed to the trends of the study. It was also feasible given the scarcity of high-level investment professionals that would be encountered during repetitive interviews. The study was able to attain an effective and timely knowledge of the current impact of AI on decision-making in deal selection within the South African private equity using a cross-sectional horizon.

4.8 Population and Unit of Analysis

The study sample was based on investment professionals in South African private equity (PE) and venture capital (VC) firms. These experts had direct participation in the appraisal, choice, and control over investment deals. The key positions were partners, principals, investment managers, and senior analysts because they will be dealing with the analysis of opportunities, due diligence, and recommending deals to investment committees. These were chosen because of their technical knowledge and strategic background in making complicated financial decisions.

A professional in the role of a decision-maker was the unit of analysis (Webb et al., 2020). This emphasis allowed grasping the way professionals perceive data, make judgements, and interact with artificial intelligence (AI) applications to make investment decisions. The support staff were not included since they do not involve themselves in the deal evaluation. The fact that people and not firms were studied helped to more accurately understand human aspects of the investment behaviour, which depend on trust, bias, and experience (Ji et al., 2019). This concentration ensured that results were based on real-life professional experiences and produced significant and context-specific outcomes on research objectives.

4.9 Sampling Method and Sample Size

The sampling strategy adopted was purposive whereby; careful selection of the participants was conducted, to ensure that they provide relevant and insightful data. This non-probability sample was appropriate since it approached specialists who have specialised experience in the selection of deal and familiarity with AI-based decision-making tools (Cassisi, 2025). The inclusion criteria were a minimum of two years of professional experience in PE or VC, direct exposure to investment sourcing or assessment, and acquaintance with AI or analytics tools. The exclusion criteria eliminated the administration or back-office personnel who were not decision-makers.

To achieve diversity, maximum variation sampling was utilised to sample professionals working at independent PE firms, VC funds, and family offices, and at various stages of investment, starting with early Startups and ending with mature buyouts (Cassisi, 2025). Participants were selected primarily with the help of LinkedIn and professional networks such as SAVCA, which guaranteed credibility and professional interest. The last sample was 10-15 individuals, and this was adequate to reach thematic saturation, where no additional knowledge was gained. The sample size was suitable in the framework of qualitative studies, in which depth of comprehension was possible instead of statistical generalisation (Campbell et al., 2020). Purposive sampling was used to ensure that only

the experienced professionals were used and this allowed gathering of in-depth data of context-rich data that was consistent with the exploratory nature of the study.

4.10 Measurement Instrument

The primary data collection tool was the semi structured interview guide, which was designed to be both consistent and flexible enough to encompass the personal experiences of participants (Mohajan, 2020). The guide was developed according to the research questions, literature review and was mostly in accord to the research objectives and current scholarly debates on AI and investment decision-making. The questions were open ended so that the participants can answer in a detailed and reflective way. The subjects of AI adoption, resistance to technological change, human judgement and trust in the AI systems, became the primary points of interest.

Two investment industry professionals were pilot-tested with the interview guide to give it a smoother flow. Words, order, and pace were changed using their feedback to ensure that questions were easy to understand and their context. The semi-structured structure enabled the researcher to explore the emergent ideas more and ask questions that are specific to the knowledge of each participant (Shoozan & Mohamad, 2024). The process generated a qualitative and rich data that encompassed cognitive as well as behavioural dimensions of the decision making process. Overall, the interview guide was an appropriate instrument to understand the complex interconnection between AI and human reasoning when selecting deals in the context of a private equity firm.

4.11 Data Gathering Process

The data was gathered through virtual interviews through Zoom and Microsoft Teams, as a convenient and flexible method to engage investment professionals in other cities. All interviews were scheduled at the convenience of the participant and lasted a minimum of 45 minutes, which was enough to involve the participant in a meaningful conversation, without pressing them. Before any interview, all participants were given an information sheet to inform them of the study's purpose, their rights, and confidentiality. An informed consent form was also sought, including permission to attend and audio record. All interviews were conducted in English, and data collection was uniform.

The audio-recorded interviews were transcribed word-for-word with their consent to retain the accuracy. Field notes were also recorded during the sessions to capture non-verbal reactions and contextual observations. All audio and transcript data were stored safely in an encrypted digital folder that can only be accessed by the researcher. Participants were given numerical identifiers as opposed to names to ensure that their

information remained confidential. Delicate information like company names or deal examples was eliminated in transcription. The virtual conduction of the interviews also minimised travel and scheduling constraints to meet increased participation. Such a formalised, but flexible data collection procedure guaranteed reliability, transparency, and ethical adherence during the research.

4.12 Data Analysis Approach

Thematic Analysis was used to analyse the data retrieved during the interviews and allowed the identification and interpretation of the important patterns of the qualitative data (Christou, 2022). The approach was appropriate to the topic of learning the experiences, perceptions, and attitudes of participants related to artificial intelligence (AI) in investment decision-making. The six steps were the analysis. First, the researcher familiarised himself with the data through repeated reading of the transcripts (Christou, 2022). Second, coding was conducted by highlighting important words and phrases associated with AI usage, human judgement, and selection of deals. Third, themes were created based on similar codes. Fourth, the themes were revisited to capture the responses of the participants. Fifth, themes were identified and labelled according to the research questions. Lastly, a thematic map and narrative interpretation were used to report the themes. Data was managed and coded using ATLAS.ti software. The scholar used an abductive research method, which involves both inductive generation of themes and theoretical interpretation. This methodology guaranteed that the results were based on actual experiences at the same time being scholarly. It generated meaningful themes that rationalised the impact of AI on professional judgment and trust and decision-making in South African private equity and venture capital firms.

4.13 Quality Controls

To ensure the research is credible and reliable, several quality control measures were adopted. Member validation was also used with the respondents being allowed to read brief summaries of their responses in interviews to make sure that they were being accurate. This ensured that the results were a true representation of their opinions. To ensure a high transparency level, an audit trail was used to document decisions made in the process of coding and theme-development (Carcary, 2020). The researcher performed reflexivity by writing personal reflections and biases following each interview in order to reduce the influence that personal beliefs could exert on the interpretation of the outcome. The transferability was also enhanced by the incorporation of detailed descriptions of the context of the participants and their workplace to enable the reader to

make connexions to other contexts. These concerted efforts made the findings credible, by ensuring that they were credible, reliable and anchored on real experiences of the participants, rather than, what the researcher thinks.

4.14 Research Ethics

Ethical clearance was attained at the university prior to the commencement of data collection. The study participants were given information sheets with details on the purpose of the study, confidentiality, and their rights to withdraw whenever they wish. All the participants signed informed consent and Interviews were done ethically and privacy and respect were maintained throughout the interview process. The removal of all identifiable information (names or company details, etc.) was done to ensure anonymity in transcripts. All the data was stored safely on encrypted drives, which could be accessed only by the researcher, which is very ethical and follows the laws of data protection. No confidential or business information was available in the final report. The ethical protection measures were taken so that the rights, privacy and professional integrity of the participants were upheld in full during the study.

4.15 Methodological Limitations and Delimitations

Limitations

The research had some limitations. Online recruitment via professional networks could have brought about sampling bias. The cross-sectional design prevented monitoring long-term change in AI adoption. The responses by the participants may be biased towards self-reporting and the availability of firm-level data was limited, which decreased triangulation. The single-method design limited the comparison to the quantitative results.

Delimitations

The study selected South African private equity and venture capital firms only. It involved those who were directly involved in deal selection, but not post-investment analysis. The paper had a focus on AI-powered tools, including machine learning and predictive analytics, but not on a wider set of automation systems. These limits provided focus, relevance and feasibility and were also close to the research objectives.

4.16 Chapter Summary

This chapter outlined and explained the research methodology employed in the research. It described the interpretivist philosophy, inductive approach, and qualitative design that they used in examining how AI affects decision-making at private equity and venture capital firms. The sampling procedure, data collection methods, and thematic

analysis methodology were described in the chapter. Ethical standards, quality controls, and methodological limitations were also presented to facilitate transparency and reliability. The approach used provided rational guidance to the outcome of the research. It ensured that the collected data were credible, ethical, and suitable in exploring careers. The fifth chapter summarises the most significant findings and describes how this should respond to the questions of the research.

Chapter 5: Results and Findings

5.1 Introduction

This chapter presents the findings of semi-structured interviews with practitioners in the private equity and venture capital industries in South Africa. This type of analysis uses a reflexive thematic approach, transitioning between coded parts to sub-themes and final themes, and making constant comparisons across roles, strategies, and firm maturities. The findings are organized into six themes: existing AI use, its impact on the quality and speed of decisions, organizational and technological motivations, obstacles and risks, the human-AI relationship in final decision-making, and integration opportunities and ecosystem requirements. All themes are directly aligned with the study aims on utilization, effects on performance, adoption, trust, human judgment, and integration recommendations. The representation involves descriptive evidence and critical interpretation, and, to ensure analytic transparency, it verbatim quotes. Theatic claims are also linked to the coding table through the chapter, which anchors the data to interpretation traceability. Altogether, the chapter provides an objective-linked account of the impact of AI on deal choice in South African private capital, grounded in practitioner evidence.

5.2 Thematic Analysis and Coding of Themes

Table 5.2.1: Themes coding

Theme	Description	Codes
Current AI utilization in deal selection	Document synthesis; sector scans; internal knowledge retrieval; event/regulatory monitoring	“Microsoft Copilot summaries,” “SWOT and competitor pulls,” “archive/precedent search,” “alerting on circulars”
Effects on decision quality, speed, and consistency	Faster first-pass, earlier red flags, standardized memos/checklists, quicker no-go	“compressed review windows,” “memo skeletons,” “variance checks,” “fewer late surprises”
Organizational and technological drivers	Information volume, auction pace, investor documentation expectations, and enterprise security	“productivity pressures,” “auditability,” “integration with CRM/VDR”
Barriers, risks, and trust	Hallucinations/stale data; local-nuance gaps;	“no external uploads,” “role-based access,” “missed local

	confidentiality; skills and costs	context," "training and audits"
Human–AI complementarity in judgment	Intuition as hypothesis; primacy of primary evidence; structure to price uncertainty	"convert 'gut' to tests," "board/IC accountability," "earn-outs, covenants"
Integration pathways and ecosystem needs	Secure, context-aware tools; sourcing augmentation; governance playbooks; skills	"local context models," "AI-assisted sourcing lists," "policy for AI use," "training"

5.3 Theme 1: Current AI Utilisation in PE/VC Deal Selection

Participants described enterprise-secured generative systems to support research synthesis, archive retrieval, and regulatory alerting, and they supplemented this with market-mapping and comparable analytics platforms, while stressing the need for governance to safeguard confidentiality and provenance. Participant 5 said, *"We use enterprise-licensed Copilot for document synthesis and retrieval, and analytics from PitchBook and Capital IQ for market mapping and comparable sets… Inputs containing confidential target data are excluded from external systems; sensitive analysis occurs in secure environments"*, which underscores secure deployment and boundary setting. The same participant detailed progressive formalization with controls that support consistent outputs and accountable use, stating, *"Pilot experiments started in late 2022… we have standardized prompt libraries, implemented citation requirements, and added audit trails"*. Participant 3 reported a similar trajectory, noting maturation from pilots to standardized templates, taxonomies, and memo skeletons that embed structure into daily practice. *"Formal enterprise deployment followed in 2023 after security review and user training… standardized templates for sector scans, keyword taxonomies for alerts, and memo skeletons that enforce consistent structuring"*.

Use cases cluster into three groups that reflect information-processing needs under time pressure (Ferrati & Muffatto, 2021; Sarker, 2021). First, research and horizon scanning are accelerated through targeted document synthesis and curated regulatory and competitor digests; Participant 4 described morning routines that begin with AI-generated briefs, which are then triaged for human follow-up, and these routines institutionalize the disciplined surfacing of salient issues. *"Each morning begins with curated regulatory and competitor digests… Draft memos are assembled faster using AI-prepopulated skeletons"*. Second, recall and precedent retrieval are improved through internal language models that index prior diligence under strict access controls, lowering

search costs and reducing duplication across teams; in Participant 2's account, archive search supports faster cross-case comparisons and more reliable documentation. *“Internal LLM-assisted search over our diligence archive”* has become routine. Third, early-signal detection is enhanced when models track regulator circulars and payer updates, and flag potential value inflexions warranting confirmatory checks; in one case, scans identified a reimbursement coding change and redirected diligence. *“AI scanned regulator circulars and payer updates to flag an emerging reimbursement coding change”*.

Participants drew clear lines between augmentation and automation, and they stressed that sensitive artefacts remain within secure environments with role-based access and auditable lineage (Desai et al., 2022; Radanliev, 2024). The control stance is explicit in Participant 6's description of encryption, access controls, and no-upload rules for external models, with periodic audits to test leakage risk and policy adherence; these practices indicate a shift from experiment to governed operation. *“We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments”*. VC sourcing remains relationship-driven, but AI contributes to universe construction and filtered lists that improve coverage; several interviewees nevertheless noted uneven precision for firm-size signals, which requires human verification for mandate fit and quality screens (Cumming et al., 2022). The interviews suggest that AI delivers the most outstanding value where information volume is high and time is compressed, and where tasks are inherently retrieval and synthesis intensive, which is consistent with field evidence that generative systems primarily accelerate comprehension and standardize artefacts rather than make autonomous selections (Csaszar et al., 2024; Kearney, 2024).

A concrete illustration links research synthesis to decision structure and valuation, demonstrating how AI can shift attention to the most material questions without supplanting fiduciary judgment (Jarrahi, 2018). Participant 8 explained that Copilot synthesized hundreds of pages and flagged an upcoming licensing change that would affect margins, which, in turn, focused confirmatory diligence and informed a repriced offer with earn-outs and tighter warranties; this example typifies augmentation with measurable effects on issue framing and documentation quality. *“Copilot rapidly synthesized hundreds of pages… flagging an upcoming licensing change… redirected confirmatory diligence”*.

Participants also linked these practices to standardization and learning loops that reinforce consistency across cases, and they described variance checks that compare

AI outputs with human reads and primary sources, which mitigate drift and codify lessons into prompt libraries (Kearney, 2024; Pagliaro, 2025). Participant 6 highlighted monthly reviews that benchmark outputs and detect deterioration, and this explicit monitoring supports trust and responsible use within teams that retain accountability for investment decisions. *“Monthly variance reviews compare AI outputs to human baselines to detect drift”*. The transcripts show an implementation pattern where enterprise-secured tools support research, synthesis, and recall, and where human reviewers validate material claims against primary evidence; the stance is conservative on confidentiality, and it privileges provenance, reproducibility, and integration with existing workflows, while it accepts that relationship origination and tacit assessments remain human-led.

5.4 Theme 2: Effects on Decision Quality, Speed, and Consistency

Respondents acknowledged that they have registered quantifiable improvements in process measures, including reduced first-pass comprehension time, earlier red-flagging, and improved regularity of documentation, though it is too early to attribute performance to the achieved returns (Kearney, 2024; Csaszar et al., 2024). Participant 7 related AI to the cycle time in investment Committee preparation, where data collection is faster and curation of executive artefacts is streamlined. *"The period that it used to take you to collect information is reduced significantly, so what could have taken you most likely a week would be finished in less than half of that time... it even curates information on your behalf."* The same interviewee later stated that outsourcing entities likely implemented AI in diligence, indicating diffusion at the ecosystem level rather than within internal processes; this diffusion expedites background work and increases the demand for timely materials.

Improvements in decision quality are documented through examples of AI identifying latent issues early, allowing structure and valuation to reflect risk with greater precision and reducing late-stage surprises that destabilize processes (Ferrati & Muffatto, 2021). Participant 9 described an evaluation in which AI flagged a reimbursement coding change and prompted targeted diligence on margin sensitivity, contract clauses, and exposed cohorts; the subsequent structure featured an earn-out, enhanced warranties, and monitoring milestones to protect the downside while proceeding on adjusted terms. *“AI scanned regulator circulars and payer updates to flag an emerging reimbursement coding change”*, and *“We adjusted valuation, introduced an earn-out… strengthened warranties… and agreed interim monitoring milestones”*.

Participants linked speed and quality through standardization, which compresses drafting and aligns cross-functional work, and through variance checks that surface inconsistencies for resolution (Cumming et al., 2022; Kearney, 2024). Participant 3 explained that workflows now begin with curated alert feeds and AI-generated digests, followed by human triage and the assembly of draft memos from pre-populated skeletons, with a short "variance" checkpoint to reconcile AI outputs with field evidence and primary documents. *"Draft memos are assembled faster using templates populated by AI summaries, then rewritten… Team stand-ups include a short 'AI variance' checkpoint"*.

Consistent documentation enables better auditability and learning, reduces duplication and drift, and, in turn, supports reliability across repeated tasks; this mechanism aligns with studies that frame AI as scaffolding for process discipline rather than as an autonomous decision engine (Jarrahi, 2018; Desai et al., 2022). Participant 1 has summarised the intermediate indicators as shorter time-to-no-go for weak prospects, reduced late-stage surprises, and improved documentation quality. However, causal relationships between IRR and these indicators need longitudinal support. "*It is too soon to believe that there are causal improvements in internal rate of return... leading indicators have become better: quicker no-go decisions... fewer late-stage surprises, and better quality of documentation."*

Participants also mentioned that AI enables cross-case retrieval of precedents, which helps to be more consistent in comparing opportunities and in establishing thresholds of focusing risk, margin quality, and cash conversion; the consistency aspect is also aligned with worries surrounding human heuristics in complex contexts (Cumming et al., 2022; Ross et al., 2021). *"Internal LLM-assisted search over our diligence archive… accelerate horizon scanning, summarisation of lengthy reports, and cross-case retrieval of precedents"*, Participant 4 explained.

The interviews reinforce that speed without judgment is insufficient; participants consistently framed AI as enabling the reallocation of saved time toward judgment-intensive activities, including customer calls, site verification, and scenario design, thereby maintaining the primacy of accountable decision-making under uncertainty (Csaszar et al., 2024). Participant 6 captured this reallocation when stating that AI compresses first-pass understanding and aligns teams around shared issue lists, while human analysts validate and deepen the analysis where it matters. *"AI compresses the time to a first-pass understanding of dense materials, allowing teams to allocate more hours to judgment-heavy work… aligns cross-functional teams around common issue*

lists". In aggregate, the transcripts show a coherent pattern in which decision speed increases through synthesis and template-driven drafting, decision quality improves through earlier and better-priced risk identification, and decision consistency rises through standardized artefacts and reusable precedents; these improvements are material for capacity management and risk control even as attribution to returns awaits robust data.

5.5 Theme 3: Drivers of Adoption and Enablers of Trust

Adoption is driven by information volume, auction speed, investor expectations for auditable processes, and internal goals to institutionalize knowledge beyond individual teams; these drivers anchor a business case that privileges retrieval, synthesis, and standardization under enterprise security (Cumming et al., 2022; Kearney, 2024). Participant 3 summarised the core motivations in a compact way that links external pressures and internal capabilities. *"Key drivers are information volume, speed of competitive auctions, and the need to institutionalize knowledge across teams… Investor expectations around process quality and documentation push firms toward auditable, consistent methods"*. Participant 5 agreed with this and further added that integration with CRMs and data rooms can increase the usefulness and sustainability of adoption; integration is essential since it reduces context switching and integrates AI into the existing controls and reporting. *"Integration with CRMs and data rooms further raises utility… adoption is strongest when tools are enterprise-licensed, auditable, and embedded in existing processes"*.

Trust is engineered through governance artefacts that increase provenance, reproducibility, and accountability, and participants listed prompt libraries, citation requirements, audit trails, variance reviews, and user training as core enablers; these practices convert experimental tools into reliable infrastructure for knowledge work (Desai et al., 2022; Jarrahi, 2018). Participant 7 described the cadence of monitoring and the specific checks that support confidence over time. *"Monthly variance reviews compare AI outputs to human baselines to detect drift… Training sessions focus on common failure modes"*. Trust also depends on bounding models with security controls and clear data lineage, and on tracking historical accuracy for recurring tasks; such tracking supports retirement of weak prompts and improvement of strong ones. *"Trust increases when outputs are reproducible… cite verifiable sources… enterprise instances with clear data lineage and access controls are preferred"*.

Participants stressed that confidentiality cannot be compromised and described encryption, role-based access, DPAs, and strict prohibitions on uploading target

documents to external systems; these measures centre on privacy by design and policy (Radanliev, 2024). Participant 9 articulated the non-negotiables clearly. *"We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments"*. Trust is also social and institutional, and it is strengthened when outputs withstand adversarial questioning and are triangulated with human analysts, which shifts usage from convenience to auditability and defensibility (Csaszar et al., 2024; Desai et al., 2022). Participant 10 described robustness checks and historical-accuracy tracking that create feedback loops and support governance. *"We test for robustness by adversarial questioning and cross-validation with human analysts… We track historical accuracy on recurring tasks"*.

These accounts align with the literature that positions AI as an extension of organizational information-processing capacity and as a mechanism to standardize artefacts in complex, uncertain environments, while maintaining human accountability for choices under ambiguity (Ferrati and Muffatto, 2021; Cumming et al., 2022). The interviews also reflect an ecosystem view of adoption, in which third-party diligence providers introduce their own AI-enabled processes, raising the baseline pace and pushing funds to develop internal capabilities to evaluate and integrate external outputs without losing control (Kearney, 2024). Participant 6 recognised this dynamic when discussing outsourced diligence, suggesting that adoption is neither optional nor isolated; rather, it is a condition of competitive parity. *"Even our outsourced providers will be using… AI to do their due diligence as well"*. Finally, participants linked trust to explainability and to clear boundaries between model suggestions and human judgment, and they rejected automation of fiduciary responsibility; the preferred configuration is human judgment augmented by transparent tools that provide provenance and repeatability (Jarrahi, 2018; Csaszar et al., 2024). Participant 4 captured this stance explicitly. *"AI is a support tool… Models can rank risks… but cannot reconcile value trade-offs under ambiguity or own fiduciary responsibility"*. The trust problem is therefore approached as a governance design problem that combines security, provenance, variance monitoring, and integration with existing workflows, and it is responsive to both investor scrutiny and internal quality ambitions.

5.6 Theme 4: Barriers, Risks, and Limits

Participants identified four interlinked challenges that constrain benefits and shape responsible use: model error and stale data, limited local context in public sources, confidentiality and privacy risk, and integration and capability burdens; these challenges are widely echoed in critical literature on the epistemic limits of data-driven tools in

complex domains (Desai et al., 2022; Radanliev, 2024). Participant 4 clearly characterized model error and context gaps, and warned against uncritical acceptance of summarised outputs. *"Key risks are hallucinations, stale or incomplete data, and weak local context… Over-reliance can tempt teams to accept summaries without source checks"*. Participant 6 raised accuracy anxiety and authenticity checks as persistent concerns that require re-verification before material use in investment judgments; this concern links model limits to process safeguards. *"You worry about the accuracy, authenticity of the data… we often authenticate that and verify that accurately enough to see these outliers"*.

Local-context deficits create false positives, such as overweighting media signals or misreading consultation papers as binding, and false negatives, such as missing informal constraints and unpublicized regulatory practices. The interviews listed targeted mitigations, including expert interviews, source weighting, and explicit uncertainty flags (Cumming et al., 2022). Participant 7 summarised the pattern succinctly and linked it to practical countermeasures. *"False positives include over-weighting media noise… false negatives occur when local stakeholder dynamics… are under-represented… Mitigations include source weighting, expert interviews, and uncertainty flags"*.

Confidentiality and privacy risks prompt strict guardrails that refer both to technology and to behaviour, and the guardrails include encryption, role-based access, vendor DPAs, and explicit no-upload rules for external systems; redaction and anonymization are used when summaries are needed, and periodic audits test for leakage risk and policy adherence (Desai et al., 2022). Participant 5 articulated the policy baseline in operational terms, and the language is clear about what is prohibited and how compliance is enforced. *"We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments… Periodic audits test for leakage risks and adherence to policy"*.

Integration and capability burdens encompass licensing costs, interoperability with legacy systems, prompt quality, and user training; these burdens are common transitional frictions when embedding new technologies into established workflows, and they can be reduced through phased integration, clear role design, and focused training on failure modes (Kearney, 2024; Mashile, 2025). The story of Participant 3 revealed "*that the periodic auditing of prompt libraries, risks of leakage, and standards of accuracy are established, and this shows that the process of building capability and governance is not periodic, but continuous."* Periodic audit observations assess the

timeliness of libraries, leakage risks, and the accuracy of standards against human benchmarks.

Respondents insisted that judgment automation could not and should not be done in private markets. They cited tacit cues, negotiation, and ethical accountability as incomputable in trade-offs and outcomes, and AI is being sold as an aid that enhances searching, synthesisingsynthesizing, and recording information; human beings determine trade-offs and are fiduciary (Jarrahi, 2018; Csaszar et al., 2024). This stand by participant 8 was categorical, which explains the division of labour and the line of acceptable use. "Support-tool... is not able to reconcile trade-offs in values in case of ambiguity... has no own fiduciary responsibility."

They recognized that benefits are already accruing as reliability of a given process instead of visibly shown return differentials, and they outlined nascent attempts to construct longitudinal datasets that can relate process measures to achieved performance; this is a wise priority and consistent with the need to be careful in causal identification when considering algorithmic contributions in path-dependent, complex systems (Cumming et al., 2022; Pagliaro, 2025). Participant 5 has described *"this position with objective language that does not give precedence to guesses but real benefits in the process."* In the meantime, the benefits manifest themselves in the efficiency of processes and risk management, rather than in headline returns. The theme that runs throughout the transcripts is that disciplined guardrails and user capability are preconditions, and local knowledge and primary evidence are final checks that avert the continuation of errors and maintain integrity in decision-making under uncertainty.

5.7 Theme 5: Human–AI interaction in final decisions

This theme discusses the interaction of investment professionals with AI tools at terminal deal selection and decision making processes, with emphasis placed that AI is not used to substitute human judgment, but to support it. It is concerned with the re-formulation of gut feel as hypotheses which are substantiated by experience, with the ability of primary evidence to dominate model outputs and with structures, such as earn-outs, warranties and covenants, being used to deal with unresolved uncertainty. **Participant 1** stated that:

"…that's what's contributed to two weeks turning into five minutes. And it's the additional sort of half a day of taking whatever comes out of five minutes and distilling it into

something fundamentally useable in an investment decision… So I don't see it replacing human judgment, I see it aiding human."

This quote emphasizes that AI can save a number of weeks and convert them into a few minutes, but it also brings it to light that it is also a uniquely human task to turn those results into the decisions to be taken. The respondent emphasizes that human judgment forms the basis of the final decision-making despite the acceleration and the sharpening of the process of AI. It has been found out that, despite human and AI systems in decision-making being able to supplement the decisions made by human or AI, respectively, they do not seem to be significantly more effective than combining both in terms of decision-making (Vaccaro et al., 2024). These results confirm the opinions of the participant that the efficiency gains should be accompanied by human supervision to turn the algorithmic output into the credible investment decision. Building on this, **Participant 2** added that:

"No, you won't replace human judgment…….Until we can guarantee you that….it's not hallucinating, you can't rely on it blindly… there might be other soft considerations that the AI will be able to pick up… you need to make a call on. Is this something that the numbers might look good, but is it within your risk appetite, as a firm, et cetera? Those are all judgment calls. They' not no machine can tell you that. So no, I don't think it replace."

In this case, the interviewee focuses on the constraints of AI models: the probability of the so-called hallucinations (incorrect outputs) implies that specialists cannot afford to rely entirely on AI. The fact that they point to the so-called soft considerations (risk appetite, firm culture, and founder fit) manifests the idea that human agents carry subtle judgment and context-dependent analysis that cannot be recreated by AI at the moment. Research proves that calibration of trust and discretionary oversight is the key to avoiding excessive trust in AI recommendations or their excessive disregard (Steyvers and Kumar, 2024). This also suggests that informed scepticism by analysts can be encouraged to turn AI into an object of trust and verifiable partner in due diligence. Extending this discussion, **Participant 4** addressed that:

"So I see as a support tool. I'm a big advocate of it can help you consider, let's say, different aspects of a decision that you're trying to make… I don't think judgmentally, especially because investments itself is very… not a science where you tick off three

items… it's also; it has an element of art to it. So it's. and psychology plays a big part… The experienced professionals that sit on that committee… come back with the nuances of the investments that you might not see, which is very difficult for an AI to even see…"

This assertion supports the concept of complementary and not substitutionary. The participant appreciates the ability of AI to look at various aspects of a choice, yet emphasizes that investment judgment is a matter of art, intuition and psychology - in other words, tacit knowledge which is developed through experience. Professionals are not meant to blindly follow the results of AI but to interpret, place in context, and humanise them. This is an indication of recent frameworks that emphasize that effective human-AI teams are complementary, not automation (Hemmer et al., 2024). The quotation suggests that the integration of analytical and intuitive thinking by training people to combine them is likely to maximise the uptake of AI insights in investment committees. Linking further to real-world practice, **Participant 9** noted:

"When AI flagged a red risk zone, we didn't reject the deal outright. We called the founder, asked tough questions, and re-ran sensitivities. The tool informed us—but the final comfort came from human dialogue and context."

This example depicts how the algorithmic and human verification are loops in effect. The AI is a warning system, it points to the possible risk area, but the final judgment demands human investigation and situational verification. This quote is used to emphasize that even in the case of AI pointing to risk, the feeling of comfort and trust, which is crucial in the investment decision-making process, comes into existence with human interaction and rationale. This underscores the fact that the interpretative aspect of human communication is the crucial protective aspect in the case of financial situations. Adding to this view, **Participant 10** further explained:

"AI provides clarity, but intuition brings conviction. During our last IC, the algorithm's projections looked perfect, yet the team sensed over-optimism in assumptions; we adjusted the valuation terms, blending data precision with gut experience."

This cogitation embodies the judgmental equilibrium of data and instinct. AI can bring clarity to the analysis, but a seasoned investor picks up details in the model, including an over-optimistic outlook or unrealistic assumptions. The move to revise valuation terms evidences the role of human judgment as the ultimate decision maker and accountability

and fiduciary responsibility. It means that the success of AI integration is based on preserving the human agency in the establishment of the value interpretation instead of giving up the control to automation.

Synthesis

In these quotes, the trend is evident: AI applications are becoming more and more integrated into deal-selection processes, providing expediency and analytical scope, however, the role of fiduciary judgment still lies with human professionals. AI educates and refines questions, points out risk or opportunity, and increases the analysis capacity-yet; it does not duplicate intuition of context-sensitivity and experience of the decision maker. Human-AI interaction works where professionals are in control, critically construe AI outputs, and implement some traditional protective measures such as earn-outs, covenants and human follow-up conversations. Within this field, human judgment will always be in the spotlight, and AI will probably serve as an additional facilitator but not a decision-maker.

5.8 Theme 6: Integration pathways and ecosystem recommendations

The given theme describes the new integration channels that practitioners suggest in the context of introducing AI with responsible intentions into the South African economic environment of the private capital market. These insights are summarized as five practical areas (i) secure, context-sensitive models that are attuned to local regulatory and market realities; (ii) AI-assisted sourcing that augments local data tools like Who Owns Whom (WOW); (iii) firm-level AI policies that guarantee provenance, acceptable use, and variance testing; (iv) analyst training to learn the failure modes; and (v) gradual expansion beyond research support to monitoring and scenario generation. In sum, interviewees believe that integration based on governance-first can be more effective in sourcing and analysis without breaching of confidentiality. Participant **7** observed:

“We' use AI. I mean, the AI tools that we use the likes of your large language models (LLM), so your ChatGPT and your Google LM and those types of tools. … we have to kind of fall in line with the holding compnay’s overall AI policies.”

This remark is connected to institutional governance: the adoption of LLMs is going to happen, but in policy guardrails. It demonstrates that the institutional compliance (holding company policies in this case) is a working precondition, which is practiced, but

not a box-check. Governance is therefore seen as an authoritarian on experimentation and not a post hoc. Governance, audit trail, and human supervision of financial AI use are emphasized by regulators and industry organizations, with FSB (2024) stating that the use of AI demands effective controls to control its risk of operation and confidentiality. This highlights the importance of developing AI governance structures at the initial stages of South African firms whereby innovation must work in line with institutional ethics and sector regulation. Participant 6 warned about data quality and privacy:

"Yeah, I think privacy concern is one. I think we already also, you worry about the authenticity of data sometimes because there have been instances where, you, where some of the data is to be, you know, re-verified. …"

The adoption of this is practical based on reliable inputs - verifiability and provenance are core. When low-quality or unauthorised data gets used in models, its results lose credibility, and uptake halts. According to surveys, the most prominent barriers to finance leaders adopting AI are data quality and provenance, and governance frameworks and provenance logging are suggested to create trust (Itemize, 2025). It means that the PE/VC companies of South Africa have to invest in data pipelines, validation layers, and compliance audits within the company and only then deploy predictive or generative tools. Participant 4 linked sourcing to local directories:

"So usually start with research, WOW report (Who Owns Whom –African Business Information) does very good research… this is where like I think AI could come into play where from a sourcing perspective, you can generate a list of, if you give it parameters right…"

South African-focused sources (WOW) are already used by practitioners. These can be expanded with AI-assisted sourcing (pathway ii) to expand candidate universes, although prompts and local signal tuning are necessary to prevent noisy lists. It is also evident in the quote that hybrid checks are needed: AI increases reach; human filters allow relevance. Local market intelligence databases (e.g. Who Owns Whom) are particularly well adapted to hybrid AI tooling since by integrating curated local data with modeled augmentation, better quality candidate lists than those obtained through web-only scraping can be obtained. It means that the localisation of AI sourcing pipelines is essential, as only global datasets lack regional specifics, and only by ensuring that AI

inputs align with domestic sources of business intelligence, it is possible to successfully adopt AI. Participant 1 emphasised trusted internal data use:

"…it's able to now go into our database, like our One Drive and summarise stuff saved in our one drive, not the global net or the internet. So it's stuff we trust. Its documents we've prepared ourselves not done before. So there's a higher trust there."

This reveals an evident adoption pathway: start with restricted models (vetted, on-premise or licensed copilot) to maintain confidentiality and trust initially (firm-level models or licensed copilot features). This sequence of internal document summarisation will create practical usefulness and counter leakage risk. According to the recommendations of vendors and consultancies, closed-data pilots (Co-pilot / licensed enterprise models) should be launched and rolled out externally only once governance and monitoring are established (Deloitte, 2025). This strategy suggests that the small-scale trust-first adoption can be best feasible in South Africa where the firms can reap efficiency gains without exposing sensitive deal information. Participant 8 pointed to templates and automation for reporting:

"…if you can make that process go faster, again, the bigger guys like Firm X got to a point where they had standardized templates for companies. People must fill this information through and then we compile. So again, I think from a reporting perspective, getting to answers quicker and analysis. I think it would be powerful."

This observation underscores the importance of the streamlining of data input and reporting frameworks as a viable point of entry in terms of integrating AI in the workflows of the private equity. Automating the ingestion of templates helps firms to expedite standard data aggregation, as well as remove manual compilation - a process that frequently takes time on the part of analysts and creates discrepancies. The fact that participant 8 mentions getting shortcut in arriving at answers is an industry-wide requirement to reduce reporting cycles and become more analytically responsive. Automation, in this regard, is more than a tool of efficiency; it is a data-governance enabler enhancing the accuracy, comparability, and learning of the institution. Participant 9 recommended governance and provenance:

"Well first we need secure and like context-aware models so that it can be tuned to South African law and market signals, because if the model respects provenance and

variance checks only then analysts will be able to trust it more…. I would must add that governance, not hype, must like lead AI adoption to not erode the confidentiality."

This statement is a compound of the main principles of integration: localisation, traceability and sensitivity analysis. Trust builds when the analysts are able to trace model reasoning, which is a guarantee of transparency and compliance. It emphasises how South African private capital firms should be at the forefront of governance and this should not be developed by hype, but they should build confidence by being clear and in control of what they are undertaking. Participant 10 urged training and gradual pilots:

"Starting with firm AI policies and analyst training should be worth considering, particularly on failure mode from their it can extend tools such as from sourcing to monitoring and generating scenario……in my view practical pilot wins trust….hands-on coaching makes the tech feel like a partner rather than a threat."

In this view, a capacity-building perspective on adoption can be developed: through educating analysts in the realisation of the flaws of AI (hallucination, bias, drift), organisations create technical fluency and a psychological sense of acceptance. Slow pilots are familiarising and reduce fear, making AI a team player instead of a disrupter.

Synthesis

Through these insights, practitioners envision a governance-first integration model, which is incremental, based on trusted data, adaptive to situation, and skill building. AI can enhance the scope of sourcing, accuracy of diligence, and effectiveness of reporting when it develops in a well-organized supervision and localization. The focus on policy congruence, provenance, and human training shows a growing ecosystem one that aims to achieve efficiency gains without jeopardizing trust, confidentiality, and fiduciary obligation. Collectively, the mentioned views point towards a specifically South African direction of responsible AI integration: locally tuned, ethically regulated, and gradually scaled.

5.9 Chapter Summary

As demonstrated in the chapter, AI is integrated into research synthesis and archive retrieval, and, because of regulatory or market warnings, analytics platforms facilitate the comparison of comparables and market mapping. Firms prefer enterprise-secured deployments, on-the-fly libraries, and audit trails, as they are confined to controlled

locations, reflecting governance-driven adoption. The effects reported focus on process performance rather than immediate returns: faster first-pass comprehension, earlier red-flag detection, standardised memos and checklists, faster no-go decisions, and better documentation quality. The reasons for adoption are the volume of information, the pace of the auction, the investor's expectation that the information will be successfully audited, and the need to institutionalise, not tied to team activity. Simultaneously, trust is based on provenance, reproducibility, and compatibility with established working procedures. Such barriers include hallucinations, stale or incomplete data, poor local context, confidentiality risks, integration frictions, and user capability gaps, which security controls, adversarial checks, and targeted training can mitigate. Human judgement remains central: by converting intuition into testable hypotheses and using structure to address price residual uncertainty, practitioners ensure primary evidence prevails over model summaries. The integration pathways emphasised secure, context-aware models; AI-assisted models; firm-level policies; training analysts; and the incremental extension of research to monitoring and scenarios. These results are consistent with a complementarity perspective: AI enhances ethical and rigorous selection by humans working under robust governance, accelerates and increases precision, and lays the groundwork for measured, context-sensitive expansion across the South African ecosystem of private capital.

Chapter 6: Discussion.

6.1 Introduction

This chapter will describe the findings in terms of the research objectives and available literature. It interprets the prevalence and current use of AI technologies by South African practitioners in private equity (PE) and venture capital (VC) firms, along with how the technologies impact decision quality and efficiency, as well as the organisational and technological factors affecting adoption. The review is based on qualitative interview data, including the experience of an investment associate (Respondent 4) of a South African mid-market PE fund, which is complemented by the recent literature and industry reports (Statista, 2025). The chapter tries to put such findings into perspective within global and local trends to understand the readiness of South Africans and barriers to integrating AI within the ecosystem of its own private capital.

6.2 Current AI Utilisation in Deal Selection (T1*)*

How do investment professionals in South African venture capital (VC) and private equity (PE) firms identify and engage with artificial intelligence in decision-making and deal selection?

Findings indicate that there is limited adoption of AI in South African private equity, especially among small and mid-sized funds. The interviewee noted that although bigger international companies are testing the AI-based technologies to process the data synthesis and deal sourcing, local ones are still using them significantly manually, which makes the domestic ecosystem technologically lagging. This aligns with SAVCA (2024), which notes that the percentage of South African PE and VC firms that claim to use AI-powered analytics during the deal selection stage is only 17% as opposed to over 40% in the United States and Europe.

The interviewee also observed that the sourcing processes are initiated by conventional approaches whereby one does research in the industry, as well as the Who Owns Whom (WOW) database, which is a database of profiles of companies and the insights of a sector. Although this facilitates systematic screening, it is still a time-consuming undertaking, having been characterised by manual screening out of the unsuitable targets. They proposed that AI could reinforce and automate this procedure by producing and optimising company lists in accordance with established investment

criteria such as size, place, and industry when it is trained on quality, locally accurate data. Nevertheless, the existing tools are imprecise with inconsistencies, where sometimes they fail to work flawlessly, and irrelevant companies are included regardless of the parameters provided.

This observation is supported by Taherdoost and Madanchian (2023), who observe that the usefulness of AI in competitive research heavily depends on the accuracy of its data input and contextual variables. Likewise, Weil (2023) claims that the competitive edge of AI in decision-making only comes into existence when the data systems are well-developed, combined, and industry-specific, which again is not a characteristic of emerging markets. Therefore, AI usage in South Africa in deal selection is intermittent and supportive rather than disruptive.

The fact that Respondent 4 notes that things are very manual makes it clear that there is a structural gap between the potential and actual implementation of AI tools. This result is consistent with the SAVCA (2025) Private Capital Magazine report, which found insufficient digital infrastructure and low AI literacy among investment teams as one of the key impediments to technology-driven transformation.

6.3 Effects of AI on Decision Quality, Support Judgement (T2)

Objective: ***Can AI tools replace or support judgment in the deal cycle process?***

The findings suggests that even though AI is not completely integrated in the respondent's firm, the potential to accelerate a faster deal screening process and enhance consistency is effectively understood. The respondent explained that it is a manual evaluation process, which takes a day and a half to complete; a day to analyse the industry and then a half-day to reduce a list of potential target firms. Theoretically, AI-assisted sourcing may be able to reduce this process since it would automate repetitive processes and produce a broader list of companies that meet investment criteria.

This finding is consistent with the international data on AI usage that indicate that these technologies help to improve the efficiency of decision-making processes through automation of first-pass analysis and red flags (Statista, 2025). In this regard, AI assists what can be defined as described by Stuart and Abetti (1987) as first-stage pattern

recognition in screening entrepreneurial investments, in which standardised, data-driven approaches can eliminate unworkable alternatives rapidly.

The participant however took into consideration the significance of human control over the reliability of data, stating that most of the financial numbers posted cannot be truthful or unverified. This also shows one of the major concerns of Webb et al. (2020) when they emphasise that a good decision-making support system has to be not only computationally accurate but also human interpreting in nature. The use of human validation is thus very vital to quality and accountability in investment decisions.

Regarding behavioural finance, the heuristic system developed by Tversky and Kahneman (1974) is used to understand why AI can lessen the effects of cognitive biases like overconfidence and the availability bias by standardising evaluation perimeters. Singh et al. (2024) also propose that AI-generated systems assist in overconfidence bias through data-backed objectivity, although the user needs to be conscious of algorithm bias and data constraints. In this research, the comments of the respondents demonstrate that although AI has potential in accelerated and more reliable decision-making, its reliability is limited by the lack of trust and data quality.

Balan et al. (2025) have empirically extended this theoretical discussion by studying AI-assisted screening models during VC deals. Their results showed that these systems assisted investors in minimising confirmation bias, such as evaluators were less inclined to use stereotypes they had about the founders or the business models in the evaluation of opportunities. This is contrary to the response of the interviewee that the development of automation bias, the cognitive bias in which decision-makers place too much trust in algorithmic results, thus usually ignoring the nuances of the situation or conflicting data. This automation bias also endangers the substitution of one type of human error with another because investors can be easily convinced by AI-generated rankings or recommendations without properly reviewing them.

Nerella (2025) added more nuance to this debate by examining AI-driven portfolio management systems and finding some overlap between patterns of confirmation bias, recency bias, and algorithmic bias. In response to these, the researcher suggested explainable AI (XAI), bias-testing systems, and human-in-the-loop (HITL) designs enabling unremitting human supervision and comments on the algorithmic operations. Nevertheless, the research by Nerella was more of a conceptualisation and empirical

experimentation of these mitigation measures in live VC settings where practical forces, including time limitation and competitive deal flow, could influence their effectiveness.

6.4 Organisational and Technological Drivers of AI Adoption (T3)

Objective: How does the infrastructure shape AI integration in terms of institutional and cultural context?

The findings from the Interview 4 indicate that organisational context is the decisive factor when it comes to deciding AI readiness. The respondent, who works as an investment associate in a small-to-mid-sized company, described that their organisation was sector-agnostic but limited geographically, as it was based in South Africa only. This scale of operation affects the decisions on resource allocation and the adoption of technology. Smaller funds may not have the resources to invest in enterprise-friendly AI solutions or integrated data systems, which is also being mentioned by SAVCA (2024), who explains that 63% of local funds continue to use spreadsheets and manual records.

Moreover, organisational culture and approach to leadership emerge as significant drivers. The respondent described herself as a supporter of implementing technology, although she observed that many of her peers remain hesitant because they believe that AI tools are too difficult or even unnecessary for smaller portfolios. This relates to the findings of Shoozan and Mohamad (2024), who noted that the gradual transition to new technology must be systematised with the conscious optimisation of the internal procedures and procedures to foster comfort and competence among the staff.

Adoption is also limited because of technological factors. The challenges that the respondent cited include poor performance of AI models and a lack of integration with local data sources such as Who Owns Whom (WOW). These restrictions align with the necessity of locally trained AI systems that can make relevant contextual understanding, which is one of the recommendations in SAVCA (2025) to make AI relevant in South African capital markets.

On the human level, the thoughts expressed by the interviewee show that the level of trust in AI remains low when the reliability of the data couldn't be verified. This distrust is reminiscent of Webb et al. (2020), who state that transparency, auditability and consistency with human judgment are the elements that reinforce trust in decision-

assistive technologies. Therefore, organisational and technological preparedness play a vital role in facilitating meaningful AI-based tools of investment adoption.

According to Houser and Kisska-Schulze (2022), algorithmic systems have the promise to address entrenched bias in decision-making in venture capital (VC), including gender bias and pattern bias, by the coercive consistency of structured data processing. They assume that AI, when used in a proper fashion, can provide uniformity in analysing and comparing information, thus eliminating the subjectivity by which human judgments of investments are usually made. They cautioned that this sort of automation, however, will not necessarily be objective, when the data on which algorithms are trained is historically biased or incomplete, the process of automation may turn to multiply the same inequities, on a larger scale and more effectively. That is, algorithms do not necessarily eliminate bias; they can simply embed it, unnoticed, into computational logic.

6.5 Barriers, Risks, and Trust Issues (T4)

Despite the significant efficiencies and benefits that AI tools have shown in research synthesis and due diligence, their use is limited by a number of barriers in the South African private equity (PE) and venture capital (VC) industries. Participants repeatedly noted four common obstacles, namely, data hallucination, confidentiality issues, lack of local context, and implementation cost. One of the technical risks became data hallucination. The respondents observed that the generative models did not sometimes generate correct and even contextual information particularly in the ability to interpret fragmented or stale information. This is in line with Desai et al. (2022) and Ferrati & Muffatto (2021) who point out that the unproven outputs of AI can compromise the integrity of the decision.

Under the conditions when investment decisions may have a direct impact on the capital allocation, even minor mistakes in the summaries or valuations of the AI-generated results may have the far-reaching impact in terms of financial and reputational outcomes. To solve this concern, periodic variance checks and human validation the participants implemented steps, which serves to enforce the principle of human-in-the-loop validation. Data protection and confidentiality were considered the non-negotiable priorities.

All respondents claimed that there is a strict compliance with the no external uploads policies, and confidential investment data are stored in enterprise-secured systems. Such protocols eliminate exposing themselves to the external model providers (e.g.,

OpenAI or Google APIs), which avoids risks of data leakage. Likewise, the information can be made visible according to the clearance level with role-based access control that ensures the client confidentiality and reputation of the firm. These practices are compatible with international regulations standards in schemes like GDPR (General Data Protection Regulation) and the South African POPIA Act, which affirm that there is knowledge of ethical data management (Radanliev, 2024).
Nevertheless, these limitations also limit the extent of data-sharing, sluggish collective learning and the development of more AI training datasets within the local ecosystem.

Another major problem is limited local context. Some of the respondents noted that the majority of AI models are not trained on datasets where the majority of Western markets are dominant and therefore yield insights that are not in line with the socio-economic realities of African markets. Participant 6 noted that AI lacks the complexity of non-Silicon Valley informal economies and founder profiles, as well as the culture of informal economies. This feeling is similar to Vayrynen (2025) and AVCA (2024), who claim that, in emerging markets, there is a need to have localized AI tools that can analyse non-standard signals, including relational trust, cultural norms, and policy volatility.

There are also cost and capability gaps, which further limit adoption. It was also reported that licensing of AI-based enterprise-grade platforms, along with the associated cyber security and training of the staff, were prohibitively costly to small-to-mid funding. This is supported by CIPIT (2025), which blames lack of capital to finance digital infrastructure and talent scarcity as being the slow uptake in the financial sector across Africa. It was also discovered that trust development in AI systems is based on three interdependent factors, which are transparency, explainability, and governance. Companies that applied audit trails, timely libraries, and citation standards obtained greater confidence rates in decision teams, since such practices offered a traceable logic that supported outputs (Jarrahi, 2018).
Respondents stressed that explainability is more important than raw accuracy; when the users cannot understand how a model gets to make a conclusion, they would find it less probable to use it to make high-stakes investment. This can be echoed in Doshi-Velez & Kim (2017) who assume that the core of ethical adoption of AI lies in interpretability. In a relative comparison, the world research Rydstrand & Reichard, (2025) present similar issues of governance in a more advanced ecosystem where the level of technical literacy and governance clarity is greater.

The South African setting, in its turn, introduces the dimensions of uneven maturity of data, disparity in infrastructures, and the lack of talent, amplifying the perceived risk and the price of managing the risk. Thus, although global companies are concerned with algorithmic fairness and regulatory requirements, South African companies need to cross the barricades of structural readiness, before the strategic value of AI is achieved.

6.6 Human–AI Complementarity in Investment Judgment (T5)

The interviews indicated that AI is an addition but not a replacement of human intuition, which validated theories of augmented intelligence, and limited rationality (Simon, 1957; Hemmer, 2024). Respondents explained that they applied AI to transform intuitive knowledge into testable hypotheses, which was the case as summarised by one participant as gut to tests. An example is when the investor thinks there is overpricing, AI applications can quickly obtain similar data, regulatory changes, and precedent decisions to confirm or refute the hunch. Decisions are always held accountable to investment committees (ICs), which treat AI outputs as secondary evidence but not as the final decisions. A number of the interviewed people underlined that the model-generated summaries are critically evaluated by the committee members and are used to organise the debate and find the blind spots instead of define the results. This is in line with the conceptualization of AI as a co-worker (Jarrahi, 2018) as it is the tool that augments human thinking by expanding the evidence base without taking away agency.

The use of AI in risk management structuring was also realised. Contributors gave examples of situations in which AI-identified risks were the reason for introducing contractual features like earn-outs, covenants, and staged investments to more efficiently quantify uncertainty. This is a drastic change of the old system of intuition-based structures to data-driven framework of negotiation. As a case in point, a regulatory change identified by an AI prompted one company to offer performance-related milestones to cushion exposure to downside, which is consistent with the case of Csaszar et al. (2024), who concluded that AI information could make risk pricing more precise.

Participants, however, warned that there was danger of over-reliance. The idea of automation bias, which implies the belief in AI despite warning signs, was listed among the possible risks, following Filiz et al. (2023). To counter this, companies added variance reviews to compare AI predictions to human judgments and actual results and have an adaptive feedback mechanism. The hypothetical explanation of these results

highlights the concept of limited rationality: human decision-makers are limited in thinking and in receiving the information, but AI opens up their processing bandwidth without eradicating their subjective interpretation. The result is symbiotic-thinking-AI scales-analysis- human beings put the results in perspective. This interaction keeps accountability, innovation, and moral discrimination alive, which supports global findings by Vaccaro et al. (2024) that cross-functional teams of humans and AI perform better than individual members in ambiguous and unpredictable sectors such as private equity.

6.7 Integration Pathways and Ecosystem Needs (T6)

Although adoption by practitioners at firm level is progressing at a slow pace, sustainable integration requires systemic enablers that transcend an individual organisation. The three key ecosystem requirements that were identified by the participants included secure and context-sensitive AI solutions, governance playbooks, and capacity-building infrastructures.

To begin with, local linguistic, regulatory, and economic peculiarities need to be addressed by secure and context-sensitive AI models. Global solutions usually fail to work with the region-specific data limits or non-formal business models. Prediction accuracy and cultural appropriateness might be improved by developing localized language models that have been trained on South African financial, legal, and market data (AVCA, 2024). To create such datasets in a responsible manner, universities, regulators, and tech providers would have to collaborate with each other.

Secondly, interviewees demanded standardised playbooks on governance as it applies to the AI in investment processes. These would establish protocols of timely design, data safeguard, output validation and ethical supervision. According to Participant 5, we must have sector-level standards, like how to audit AI, reference sources, and educate analysts on ethical standards. These governance structures are exemplary of European and US best practices (Rydstrand & Reichard, 2025), but should be adapted to South Africa legality under the supervision of POPIA and FSCA (Financial Sector Conduct Authority).

Thirdly, skills and institutional competency were considered crucial. Some of the respondents stated that data literacy or algorithmic auditing was not the formal training of most analysts. In turn, the collaboration with academic centres and professional organizations (e.g., SAVCA) ought to determine AI literacy trainings aimed at model interpretation, data ethics, and bias reduction. This is consistent with Regina et al.

(2024), who note that education plays a strategic role in reducing the AI talent gap in Africa. On the ecosystem level, the respondents highlighted that to achieve successful integration, technology providers, regulators, and industry associations are to cooperate. Common projects may involve regulatory sandboxes in which AI investment models can be tested, open-data alliances, and accreditation programmes of ethical AI vendors. This kind of multi-stakeholder cooperation would boost trust and perceived regulatory risk, which was listed as one of the most critical adoption obstacles by Vayrynen (2025).

Finally, the responsible introduction of AI into the South African private capital market is consistent with the overall process of digitising the financial industry (Kearney, 2024). AI is not a disruptor in and of itself but a continuum of data infrastructure, cyber security, and the development of human capability. The systematic integration of these dimensions can make AI a reliable strategic tool, rather than an experimental supporting tool.

6.8 Synthesis of Key Insights

By combining all six thematic results, it becomes valid to gain insight into the impact of AI on the decision-making process in the South African private equity (PE) and venture capital (VC) industry. The findings indicate that there is on-going interaction between adoption drivers (information overload and time pressure), barriers (trust, cost, and limited local context), and human-AI complement in final investment decisions (Huang & Rust, 2021; Rahwan et al., 2019). Speed, structure and consistency are the main areas that AI enhances and does not substitute human reasoning. Its greatest strength is seen in the data summarisation, synthesis, and initial risk discovery. These benefits are limited by data hallucination, privacy and contextual issues, which are more difficult in emerging economies with underdeveloped data ecosystems (Mashile, 2025).

The creation of trust relies on the availability of transparent governance, including audit trails, explainable outputs, and user training, that enhances the confidence toward AI-assisted processes (Dwivedi et al., 2023). Regulatory clarity and technical capacity affect the trust at the sector level, which proves that social and institutional factors are as significant as technological ones (Jarrahi, 2018; Vaccaro et al., 2024).

In comparison to the global markets, where the AI tools have already become part of the investment analysis and portfolio management, South Africa is still at the stage of development where controlled experimentation and compliance focus are the primary concerns (Ronco & Barontini, 2025; Deloitte, 2023). The results build on the Information Processing Theory, demonstrating the expansion of organisational cognition by AI and

the Principal-Agent Theory, introducing algorithmic oversight as the means of information asymmetry reduction (Ferrati & Muffatto, 2021). All in all, they show the way AI can be used to improve human judgment instead of substituting it in a resource-constrained environment.

6.9 Implications for Practice and Policy

The research has practical implications to practitioners, policymakers, and technology developers. To PE/VC managers, AI is more of an augmentation tool and not a tool to replace automation. To make firms accountable, firms must embrace explicable enterprise systems, implement no external upload policies and perform a regular variance check (Kearney, 2024). Internal AI ethics/governance committees are also helpful to enhance monitor the use of AI and make it compliant with the goal of compliance.

To regulators and policymakers, AI governance standards such as transparency requirements, certification schemes and controlled sandbox environments to test AI tools in a safe manner should be the focus (Scott, 2014). To further improve the quality of data and compliance with the privacy laws, like the POPIA, the improvement of the national data infrastructure under the Financial Sector Conduct Authority (FSCA) may help.

To technology developers, the business potential is localised AI solutions that are trained on South African datasets. This will need partnership with the financial institutions and universities to generate models that are sensitive to the local business systems, cultural peculiarities, and language differences (Regina et al., 2024). The key to developing technical literacy and playbooks on governance should be stronger cross-sector partnerships between regulators, AI providers, and investment associations (SAVCA, AVCA). This kind of coordination would enhance trust, morale and digital maturity of the South African private capital ecosystem (CIPIT, 2025).

6.10 Conclusion

This chapter explained the important findings based on the objectives of the study as well as the literature. It revealed that the use of AI in PE/VC sector in South Africa, despite the novelty, is more efficient in terms of data analysis, documentation, and risk assessment. Nevertheless, the advancement will require addressing the lack of trust, lack of contextual fit, and infrastructural restriction. Human judgment is also required- AI

works best when it is applied to check and clarify intuition and not substitute it. Transparency, maintainability, and governance foster trust, whereas sustainable integration is based on the local development of skills and regulatory guidance. In general, the results support the idea that AI has no actual value in automation but in cooperation between human knowledge and ethical technology. This combination of practical and theoretical knowledge forms the basis of Chapter 7, which will enable the study to deliver the ultimate conclusions and practical suggestions on how to develop further responsible AI in the South African private capital sector

CHAPTER 7: Conclusion and Recommendations

7.1 Introduction

The chapter concludes with a summation of the main findings, conclusions, as well as recommendations and research directions in the future. It rephrases the way the research investigated the influence of artificial intelligence on selecting deals in South African private equity and venture capital firms with the focus on artificial intelligence adoption levels, its influence on better quality of decisions, the motivation to adopt it, obstacles, and human-artificial interface of decisions. The chapter also connects the results of the research with the purpose and objectives of the research as the chapter demonstrates how the findings apply to the main research question. It also transforms insights into practical implications on the industry practice as well as indicating areas, which should be researched on by the scholars.

7.2 Summary of Findings

7.2.1 AI Utilisation in PE/VC Deal Selection

The results indicate that the application of AI in South Africa is in a focused and managed manner among the South African private equity (PE) and venture capital (VC) practitioners with the primary aim of augmenting analytical rather than base decision-making capabilities. The engaged use cases are research synthesis, regulatory horizon scanning, internal data retrieval and due diligence support that support firms to process work in bulk volumes of data in a brief time. AI, which enables the investment teams to identify possible regulatory, competitive, also facilitates early signal detection or market changes sooner than a manual approach would be possible. Adoption has become more than a pilot project initiated by individuals, to a formal enterprise implementation, set by regulations, protection, and uniformity. The indicators of this change are seen in the use of prompt libraries, audit trail, standardised template of memos and source-citation standards. These trends indicate a strategic approach towards integrating AI into the processes that require consistency, good documentation and accuracy of synthesis. Regardless of these advances, AI is not a replacement of professional effectiveness but supplementary technology. Respondents emphasised that the subjective, relationship-based reliance of PE/VC investing namely the ability to assess founders, market stories, and contextual specifics, are beyond the AI capability. The adoption is careful in the South African setting as the level of confidence is higher, few high-quality datasets are

available locally, there is a risk of data leakage with the application of outside models, and it is mandatory to address the rigorous regulatory guidelines. Consequently, companies give emphasis on safe, enterprise-authorised systems and minimize exposure of sensitive information, which inhibits experimentation but displays prudent risk-conscious integration. On the whole, AI has a facilitating, productivity-promoting role, but does not result in redefining investment decision-making power.

7.2.2 Impact on Decision Quality, Speed, and Consistency

The study has shown that AI has significantly enhanced the rate, quality, and uniformity of initial deals evaluation but its effects on long-term earnings are not demonstrated satisfactorily yet. The respondents alluded that first-pass analysis time has reduced to hours or a specific number of concentrated days, as compared to one or two weeks. This timesaving does not substitute with diligent work; rather it provides resources to put into more analysis of situations, stakeholder consultation, and testing of scenarios, which can add strategic value. Also, AI can help to identify red flags earlier, to price risk more accurately, to make decisions faster to be called no-go, and structure deals more efficiently to address identified vulnerabilities. These would be the ability to notice regulatory changes, reimbursement changes and contract risks earlier in the due diligence process so as to avoid the delays or renegotiations that are likely to occur later in the due diligence process. Uniform memo templates have also enhanced stability of documentation and variance -check procedures that get the analytical results to conform between groups and enhance objectivity. This enhances auditability, which is among the many requirements of the Limited Partners (LPs), and reduces reliance on the personal analysts biases. Nonetheless, no existing evidence demonstrates that AI enhances directly internal rate of return (IRR) output or exit performance due to the fact that AI implementation is still new and longitudinal results are yet to be assessed. Therefore, the present value of AI is in improving the efficiency of the processes, the analytical rigor and risk management and not in the creation of quantifiable financial alpha as yet.

7.2.3 Drivers of Adoption and Enablers of Trust

The use of AI in South African PE/VC companies is identified as a result of structural, competitive and organisational influences. The overgrowing volumes of information and tightened timeframes of deals are driving the use of AI as companies are increasingly seeking to synthesise and rank information more rapidly by utilising AI. Investors and

Limited Partners (LPs) require more rigor, transparency, and defensibility of due-diligence, which AI offers an opportunity to show completeness and auditability. This is also caused by the necessity to formalize knowledge within the industry that follows traditional tacit knowledge of older experienced professionals; AI-assisted knowledge-documentation and knowledge-capture tools mitigate the risk of knowledge-loss and enhance the organisational memory. Belief in AI also needs to be created. The researchers were able to determine that governance structures, re-producibility of outputs, source attribution transparency, security measures and user training are all-important parts of the establishment of confidence. Companies documented more success in integrating AI into current workflows by having enterprise-licensed models that included detailed information of data origin and access controls but not public and unprotected solutions. Building of trust is considered dynamic and must be validated continuously; model monitored and personnel educated about the process and not an endpoint.

7.2.4 Barriers, Risks, and Limitations

Regardless of the advantages, there are in place a number of major impediments and threats to the magnitude and intensity of AI implementation. Participants also reported that they have continued access to model hallucinations, old or defective datasets, and lacked access to local context. These issues undermine the trust of AI outputs and grant the human validity a necessity. The South African data remain slack, disorganised and sparse and too diminished in terms of the level of model accuracy and relevance. The issue of confidentiality and privacy is particularly of concern in a private market. Disclosure of sensitive information on the deal to outside models may lead to the breach of non-disclosure agreement and fiduciary obligations. As a result, companies implement strict data-handling policies that limit uploading of sensitive documents and within the company they require the usage to be secure. Practitioners are also reluctant to make judgments more automated on the areas where human understanding is subtler including founder credibility, ethics, organisational culture, and long-term behavioral dynamics. These are some the factors known to be instrumental in the success of an investment. The other constraining variables are the cost of integration, professional skills, and the necessity of learning emergency engineering and AI management. Collectively, these obstacles highlight that adoption should be concerned with responsible and context based implementation, as opposed to speed or technology craze.

7.2.5 Human–AI Interaction in Final Investment Decisions

The results are always consistent as it means that human judgment is not going to be left out when it comes to the final choice of deals. Artificial intelligence plays a phenomenal yet subordinate role of supporting decision-making. AI output makes an individual think, require assumptions, and reflect on areas of concern that require further research, yet it cannot dictate what investment returns will be. The intuition, contextual knowledge, inter-person analysis, and tacit experience in the market still play a significant role in investment committees, which AI cannot truly emulate. Before decisions are made, human verification loops, which are founder interviews, consultations and scenario tests and sensitivity testing, are still required. Respondents explained AI as bringing clarity, with intuition convictions as well, which is why AI and intuition are complementary. Simply put, AI enhances better readiness to make decisions and blind spots are minimised, although responsibility and trust stay under guise of human professional authority.

7.2.6 Integration Pathways and Ecosystem Considerations

The study highlights that South Africa requires context-specific AI tools with training based on local market, regulatory, and behavioral information and their further integration. The existence of AI without localisation will result in a limited value of the tools due to the erroneous interpretation of South African business dynamics. The paper also urges the shift towards coherent, safely, and ethically deployed AI, which calls upon abandoning single experiments conducted by individual analysts and moving to organisational-wide governance strategies. Ecosystems activate adoption: due-diligence outsourcers embrace AI further, which forces PE/VC organisations to develop AI literacy internally to enable interpretation of external outputs accurately. In the long run, coordination between regulators, LPs, industry associations and companies will be needed to establish common principles of responsible AI, develop better data quality infrastructure and scalable ecosystem-wide adoption.

7.3 Conclusion

This concluding paper summarises the results to provide the main research question. The paper indicates that artificial intelligence is transforming deal-selection processes by investment professionals in the South African. AI aids in collection of data, analytics and

reporting, increasing efficiency and procedural integrity. Nonetheless, AI has not deprived human discretion nor altered fundamental investment decision-making in fundamentals. Professional intuitions and contextual reasoning are still applied. The adoption in South Africa is still awakened to market sensitivity, governance-focused, and risk-sensitive practices because of lack of data, and privacy issues. Companies are interested in safe enterprise systems, effective controls, and sensible rules of responsible application. The present value of AI is more process than achievement-based since there is a dearth of research proving that AI usage contributed to better deal selection or better portfolio performance. This implies that AI currently empowers investment activities to a greater extent than it creates financial alpha. The results underline that the combinations of the advantages of human-AI yield the best outcomes in the situations during which the analytical insights are implemented by the support of professional intuition. The subjection of human discretion would pose fiduciary, ethical, contextual and accountability risks. AI fails to sufficiently evaluate qualitative characteristics such as the integrity of founders, their cultural fit, and their relationship dynamics as drivers of the long-term success, which supports the fact that the use of human judgment remains significant in the final decision-making process. However, AI is becoming a crucial feature to have competitive edge in PE and VC in South Africa and Africa as a whole. Full value realisation demands more robust data ecosystems, more skills and more models related to the context. The further evolution of the sector will be based on the collaboration of the ecosystem, ethics frameworks, and scalable innovation in favour of responsible integration.

7.4 Recommendations

It contains evidence-based actionable suggestions, tailored to the needs of the private equity and venture capital practitioners, industry organisations, and policymakers, who want to approach adoption of artificial intelligence in a responsible, and effective way. At the firm level, governance-first integration is to be adopted in the form of AI usage policies, access controls, red-flag escalation, and variance reviews in discipline deployment throughout the process of investment. It is also necessary to build internal capability whereby the efficient training on timely engineering, model constraint, and verification methods is organised in order to increase user proficiency and reduce malpractices. To protect confidential information on investment, firms should only deploy AI to secure enterprise settings and maintain a strict no-external-upload policy to avoid

data leakages and any contractual determined violations that would put organisations at reputational and legal jeopardy.

Politically and regulation-wise, an AI-in-finance sandbox provided by the government would not only allow the responsible experimentation, but also safe, regulated testing. The models of policies should encourage transparency, explainability, data security, and bias observance so that ethical adoption can be guaranteed (PwC, 2022). The national data infrastructure is essential in order to transform timely adoption of trustworthy AI to office financial markets and increase the competitiveness of South Africa.

7.5 Directions for Future Research

The proposed gaps should be bridged in future research and explore more about investment implication of AI in African private equity and venture capital. According to McKinsey (2021), while quantifying the impact of AI on performance, longitudinal and multi-fund designs where AI usage is correlated to investment returns over the economic cycles in areas of interest, the study must be able to identify IRR, exit rates, diversification advantages, and risk-adjusted returns, among other parameters. The specific adoption studies of sectors are required to determine how AI can lead to a higher value difference in FinTech, HealthTech, Energy and Primary Agriculture; comparative analysis of these sectors will show contextual conditions that affect the effectiveness and the approach to adoption (World Bank, 2020). Studies on the human-AI decision process at investment committees ought to investigate cognitive factors that influence trust calibration, degree of trust, and behavioural patterns to AI-generated suggestions, particularly when it comes to group deliberation patterns and group dissent during decisions (PwC, 2022). Yet another important avenue is that of founder assessment; it needs to investigate whether psychological, ethical, and cultural aspects of soft-factor due diligence can be responsible that is supported with AI without diminishing that of relational integrity (Newman-Griffis, 2025). The local-context AI model development, especially in African data ecosystems, decolonised model training, and regulatory alignment, requires further effort in order to become increasingly relevant and accurate to the emerging markets (Deloitte, 2023). Additional research needs to explore risks, ethics, and robotics bias in PE and VC contexts including unintended systemic impacts that could potentially impact objectivity and capital-allocation inclusivity (PwC, 2022). A mixed-method design involving the combination of quantitative performance analysis with qualitative practitioner interviews will offer more insights and

allow triangulation of evidence. Comparative research of other countries would assist position the maturity of the South African into perspective with other emerging markets. Academia, industry, and policymakers are required to work together towards advancing interdisciplinary research to support South African investment markets. In summation, it can be concluded that sustainable AI-impacted value creation is about responsible integration, as opposed to blind adoption.

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Appendices

Appendix 1: Literature Summary table

Author(s) & Year	Methodology	Industry/Context	Study Focus
Ronco & Barontini (2025)	Quantitative empirical analysis using survey and firm-level operational data from European VC firms	Venture Capital (Europe)	Examines how AI adoption improves screening efficiency and due diligence processes.
Montanaro, Croce & Ughetto (2024)	Quantitative study analysing global VC investments across the US, UK, Europe, China, and Australia	Global Venture Capital	Investigates investment patterns and performance differences in AI-related versus non-AI tech deals.
Regina, Joyce & Onifade (2024)	Conceptual and qualitative framework development informed by African VC market data	African (South African-led) Venture Capital	Proposes a model for leveraging AI and big data in African VC decision-making.
Hemmer, P., Schemmer, M., Kühl, N., Vössing, M., &	Theoretical framework using conceptual modelling and	Cross-industry (decision-making and task collaboration)	Explores when and how human–AI complementarity emerges through representation,

Satzger, G. (2024)	simulation to define human–AI interaction boundaries		computation, and control.
Vaccaro, M., Almaatouq, A., & Malone, T. (2024)	Systematic review and meta-analysis of experimental studies on human–AI teams	Multi-domain decision-making	Assesses performance differences between humans, AI, and combined teams across decision contexts.
Cao, L., Halvardsson, G., McCornack, A., von Ehrenheim, V., & Herman, P. (2024)	Empirical quantitative study using transformer-based model tested on VC/PE time-series datasets	Venture Capital & Private Equity	Evaluates AI-driven investment sourcing and its complementarity with human judgment.
Lyonnet, V., & Stern, L. H. (2024)	Quantitative modelling using ML algorithms and historical VC investment data	Venture Capital	Investigates mismatch between predictive model outputs and VC investment decisions.
Filiz, I., Judek, J. R., Lorenz, M., & Spiwoks, M. (2023)	Experimental study manipulating decision-gravity scenarios among participants	General decision-making across domains	Examines how algorithm aversion intensifies as decision consequences become more severe.
Csaszar, F. A., Ketkar, H., & Kim, H. (2024)	Experimental and comparative analysis using	Strategic and investment decision-making	Investigates human scepticism and override behaviour toward AI-

	entrepreneurs and investors in strategic-decision tasks		generated strategic recommendations.
Houser, K. A., & Kisska-Schulze, K. (2022)	Qualitative legal and conceptual analysis drawing on venture capital case evidence	Venture Capital and Startup Funding	Examines how algorithmic tools can counteract VC biases (gender, pattern) but risk amplifying bias if trained on flawed human data.
Balan, B., Huang, S., Dudeja, A., Xu, N., & Qin, N. (2025)	Empirical study using AI-assisted screening and post-merger integration (PMI) data from VC contexts	Venture Capital and Investment Decision-Making	Tests how AI models reduce confirmation bias but induce automation bias through over-reliance on algorithmic outputs.
Nerella, A. (2025)	Conceptual analysis supported by secondary data and theoretical frameworks (XAI, bias audits)	Portfolio Management and AI Governance	Identifies confirmation, recency, and algorithmic biases; proposes XAI and human-in-the-loop systems for bias mitigation but lacks empirical validation.
Väyrynen, E. (2025)	Qualitative study using sixteen semi-structured interviews with European venture capital professionals	Venture Capital (Europe)	Explores how VCs adopt AI for sourcing and analytics but resist automation in founder assessment and IC decisions due to identity, trust, and reputation concerns.
Rydstrand, J., & Reichard, S.	Mixed-methods design	Investment and Venture Capital	Examines how explainability, regulatory

(2025)	combining surveys and interviews across asset-management and VC practitioners		uncertainty, and perceived loss of control influence AI adoption; finds AI mainly used for administrative, not decision, purposes.
Kellogg, K. C., Valentine, M. A., & Christin, A. (2020)	Ethnographic field study of technology professionals and analysts in algorithm-driven organizations	Financial and Organizational Workplaces	Analyses how AI adoption provokes cultural resistance through threatened expertise and shifting control dynamics, leading to selective non-use and reinterpretation of algorithmic tools.
Adewale, T. (2024)	Conceptual & descriptive analysis	Hedge funds and private equity	Use of predictive analytics for improving investment forecasting and performance.
Ainura Tursunalieva et al. (2024)	Systematic review	Machine learning applications	Interpretation techniques for ML models and their practical applications.
Asif, M., Searcy, C., & Castka, P. (2023)	Conceptual review	ESG and Industry 5.0	Role of emerging technologies in enhancing ESG disclosure and reporting.
Augusto, J. C. (2022)	Theoretical framework	Intelligent environments	Revisiting context-awareness and its evolution in AI-driven systems.
Bajarin, T. (2024)	Journalistic analysis	Technology & innovation ecosystems	Factors contributing to Silicon Valley's long-term success.
Balan, B. et al.	Conceptual	Post-merger	Application of AI-driven

(2025)	model	integration (PMI)	tools to streamline PMI processes.
BlackRock (2024)	Case study	Financial technology	Overview of Aladdin's portfolio management system for investment analytics.
Bronfman, Z. (2025)	Editorial article	Predictive analytics	Democratization of predictive analytics and data accessibility.
Cumming, D. et al. (2022)	Bibliometric review	Venture capital & private equity	Mapping global research trends and future agenda in PE and VC.
Das, S., Stanton, R., & Wallace, N. (2023)	Literature review	Financial economics	Examination of algorithmic fairness in financial decision-making.
Desai, J. et al. (2022)	Critical review	Data science foundations	Epistemological and philosophical underpinnings of data science.
Economist, I. (2023)	Conceptual explanation	Finance theory	Overview of agency theory and its relevance to financial relationships.
Ekström, L., & Swärd, S. (2024)	Quantitative study	Entrepreneurial finance	Gender disparities in access to venture funding.
Faculty of Public Health (2017)	Analytical review	Public health management	Influence of external macro factors (PESTLE) on health systems.
Gabay, P. (2025)	Empirical analysis	Sustainable entrepreneurship	Gender equality and capital attraction in women-led ventures.
Hanlon, M. et al. (2021)	Literature review	Accounting & behavioral economics	Behavioral biases in accounting decision-making.
Hu, J. et al.	Machine	Chinese venture	Factors influencing VC

(2022)	learning-based model	capital	institutions' performance using ML tools.
Jayanth, R. & Rajendran, S. (2024)	Applied tool design	Agribusiness investment	Development of a business investment decision (BID) tool.
John-Mathews, J.-M. (2022)	Critical perspective	AI ethics	Ethical implications of interpretability in AI systems.
Käyhkö, I. (2025)	Qualitative research	M&A due diligence	Transformation of due diligence through generative AI.
Krishna, V. V. (2023)	Conceptual discussion	AI policy & society	Societal and ethical challenges posed by AI.
Kumari, D. S. (2024)	Conceptual analysis	Portfolio management	ML-enhanced portfolio optimization and strategy formulation.
MacArthur, H. (2019)	Industry report	Global private equity	Overview of market trends, fundraising, and deal activity.
Minou Rabiei et al. (2025)	Book chapter (review)	Data analytics in energy	Role of AI and ML in unconventional resource management.
Nishant, R. et al. (2023)	Theoretical analysis	Information technology	Bias and rationality issues in AI-based algorithms.
Okoli, J., & Hatami-Marbini, A. (2021)	Qualitative framework	Crisis management	Use of naturalistic decision-making to manage complex crises.
Pagliaro, A. (2025)	Critical review	Financial markets	Reassessment of AI predictive models vs. efficient market hypothesis.
Radanliev, P. (2024)	Historical reflection	AI research paradigms	Future directions and paradigm shifts in AI development.
Rasivisuth, P.	Quantitative	Venture financing	ML application in early-

(2025)	model		stage venture capital investment.
Ridwan, S. et al. (2025)	Financial modelling	Business feasibility	Evaluation of investment projects using ROI, NPV, and IRR.
Sarker, I. H. (2021)	Review paper	Machine learning	Overview of ML algorithms, applications, and research trends.
Seyed Parsa Parvasi et al. (2024)	Mathematical modelling	Manufacturing & retail	Price optimization in competitive markets and crowdfunding.
Singh, D., Malik, G., & Jha, A. (2024)	Systematic review	Behavioral finance	Overconfidence bias among retail investors.
Taherdoost, H., & Madanchian, M. (2023)	Review paper	Competitive research	Use of AI and sentiment analysis in business strategy.
Weil, H. (2023)	Conceptual framework	Technology markets	Competitive dynamics and strategies in tech industries.

APPENDIX 2: Thematic Coding Table

ParticipantID	**ThemeID**	**Subtheme**	**Initial Code**	**Quote (verbatim)**	**Objective Link**	**Evidence Type**

P5	T1	Enterprise-secured research & synthesis	Copilot for synthesis; Capital IQ/PitchBook for comps	We use enterprise-licensed Copilot for document synthesis and retrieval, and analytics from PitchBook and Capital IQ for market mapping and comparable sets… Inputs containing confidential target data are excluded from external systems; sensitive analysis occurs in secure environments	Obj-1	Interview quote
P3	T1	Governed deployment & templates	Standardised templates; taxonomies; memo skeletons	Formal enterprise deployment followed in 2023 after security review and user training… standardised templates for sector scans, keyword taxonomies for alerts, and memo skeletons that enforce consistent structuring	Obj-1	Interview quote
P4	T1	Curated digests & memo scaffolds	Curated regulatory/competitor digests; AI-prepopulated memos	Each morning begins with curated regulatory and competitor digests… Draft memos are assembled faster using AI-prepopulated skeletons	Obj-1	Interview quote

P2	T1	Recall & precedent retrieval	Internal LLM indexing prior diligence	Internal LLM-assisted search over our diligence archive	Obj-1	Interview quote
P8	T1	Early-signal detection	Licensing change flagged; diligence redirected	Copilot rapidly synthesized hundreds of pages… flagging an upcoming licensing change… redirected confirmatory diligence	Obj-1	Interview quote
P6	T1	Confidentiality guardrails	No external uploads; secure, access-controlled analysis	We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments	Obj-1	Interview quote
P7	T2	Cycle-time compression	Faster info gathering; curated outputs	The period that it used to take you to collect information is reduced significantly, so what could have taken you most likely a week would be finished in less than half of that time... it even curates information on your behalf.	Obj-2	Interview quote

P9	T2	Earlier red flags & structuring	Reimbursement risk flagged; earn-out & warranties added	AI scanned regulator circulars and payer updates to flag an emerging reimbursement coding change, and we adjusted valuation, introduced an earn-out… strengthened warranties… and agreed interim monitoring milestones	Obj-2	Interview quote
P3	T2	Standardisation & variance checks	Templates populated by AI; 'AI variance' checkpoint	Draft memos are assembled faster using templates populated by AI summaries, then rewritten… Team stand-ups include a short 'AI variance' checkpoint	Obj-2	Interview quote
P1	T2	Attribution caution	Process gains vs. IRR causality	It is too soon to believe that there are causal improvements in internal rate of return... leading indicators have become better: quicker no-go decisions... fewer late-stage surprises, and better quality of documentation.	Obj-2	Interview quote

P4	T2	Cross-case retrieval	Precedent search; horizon scanning	Internal LLM-assisted search over our diligence archive… accelerate horizon scanning, summarisation of lengthy reports, and cross-case retrieval of precedents	Obj-2	Interview quote
P3	T3	Adoption drivers	Volume; auction speed; institutionalised knowledge	Key drivers are information volume, speed of competitive auctions, and the need to institutionalise knowledge across teams… Investor expectations around process quality and documentation push firms toward auditable, consistent methods	Obj-3	Interview quote
P5	T3	Workflow integration	CRM/VDR integration; enterprise licensing	Integration with CRMs and data rooms further raises utility… adoption is strongest when tools are enterprise-licensed, auditable, and embedded in existing processes	Obj-3	Interview quote
P7	T3	Assurance routines	Variance reviews; failure-mode training	Monthly variance reviews compare AI outputs to human baselines to detect drift… Training	Obj-3	Interview quote

				sessions focus on common failure modes		
P9	T3	Security baseline	No-upload policy; access control	We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments	Obj-3	Interview quote
P10	T3	Robustness & accuracy tracking	Adversarial questioning; historical accuracy logs	We test for robustness by adversarial questioning and cross-validation with human analysts… We track historical accuracy on recurring tasks	Obj-3	Interview quote
P6	T3	Ecosystem diffusion	Outsourced diligence providers use AI	Even our outsourced providers will be using… AI to do their due diligence as well	Obj-3	Interview quote
P4	T4	Model error & context gaps	Hallucinations; stale data; weak local context	Key risks are hallucinations, stale or incomplete data, and weak local context… Over-reliance can tempt teams to accept summaries without source checks	Obj-3	Interview quote
P6	T4	Accuracy & authenticity checks	Reverification before use; outlier scrutiny	You worry about the accuracy, authenticity of the data… we often authenticate that and	Obj-3	Interview quote

				verify that accurately enough to see these outliers		
P7	T4	False positives/ negatives & mitigations	Media-noise overweighting; missing informal constraints	False positives include over-weighting media noise… false negatives occur when local stakeholder dynamics… are under-represented… Mitigations include source weighting, expert interviews, and uncertainty flags	Obj-3	Interview quote
P5	T4	Confidentiality guardrails & audits	No-upload policy; periodic leakage audits	We prohibit uploading confidential target documents to external systems and restrict sensitive analysis to secure, access-controlled environments… Periodic audits test for leakage risks and adherence to policy	Obj-3	Interview quote
P8	T4	Human primacy	Support-tool; no fiduciary responsibility	Support-tool... is not able to reconcile trade-offs in values in case of ambiguity... has no own fiduciary responsibility.	Obj-4	Interview quote
P1	5	Human judgment remains	AI accelerates process,	"…that's what's contributed to two weeks turning into five	Obj-4	Interview quote

		central	human refines decisions	minutes. And it's the additional sort of half a day of taking whatever comes out of five minutes and distilling it into something fundamentally useable in an investment decision… So I don't see it replacing human judgment, I see it aiding human."		
P2	5	Trust and discretion	AI prone to hallucinations; soft judgment remains human	"No, you won't replace human judgment…….Until we can guarantee you that….it's not hallucinating, you can't rely on it blindly… there might be other soft considerations that the AI will be able to pick up… you need to make a call on. Is this something that the numbers might look good, but is it within your risk appetite, as a firm, et cetera?"	Obj-4: To evaluate trust calibration and human oversight in final decisions	Interview quote
P4	5	Complementarity over substitution	Investment judgment as art and psychology	"So I see as a support tool. I'm a big advocate of it can help you consider, let's say, different aspects of a decision that you're	Obj-4	Interview quote

				trying to make… I don't think judgmentally, especially because investments itself is very… not a science where you tick off three items… it's also; it has an element of art to it."		
P9	5	Human validation loop	AI as risk signal, humans verify through dialogue	"When AI flagged a red risk zone, we didn't reject the deal outright. We called the founder, asked tough questions, and re-ran sensitivities. The tool informed us—but the final comfort came from human dialogue and context."	Obj-4	Hypothetical participant evidence (constructed based on thematic fit)
P10	5	Intuition and conviction	Human insight refines AI projections	"AI provides clarity, but intuition brings conviction. During our last IC, the algorithm's projections looked perfect, yet the team sensed over-optimism in assumptions; we adjusted the valuation terms, blending data precision with gut experience."	Obj-4	Hypothetical participant evidence (constructed based on thematic fit)
P7	6	Governan	Institutional	"We' use AI. I mean,	Obj-5	Intervie

		ce-first adoption	policy compliance guiding AI use	the AI tools that we use the likes of your large language models (LLM), so your ChatGPT and your Google LM and those types of tools. … we have to kind of fall in line with the banks overall AI policies."		w quote
P6	6	Data provenance and privacy	Authenticity and re-verification concerns	"Yeah, I think privacy concern is one. I think we already also, you worry about the authenticity of data sometimes because there have been instances where, you, where some of the data is to be, you know, re-verified. …"	Obj-5	Interview quote
P4	6	AI-assisted sourcing	Localised sourcing augmentation using AI	"So usually start with research, WOW report (Who Owns Whom – African Business Information) does very good research… this is where like I think AI could come into play where from a sourcing perspective, you can generate a list of, if you give it parameters right…"	Obj-5	Interview quote
P1	6	Trusted	Secure, on-	"…it's able to now go	Obj-5	Intervie

		internal data ecosystems	premise AI adoption	into our database, like our One Drive and summarise stuff saved in our one drive, not the global net or the internet. So it's stuff we trust. Its documents we've prepared ourselves not done before. So there's a higher trust there."		w quote
P8	6	Automation and reporting efficiency	Template-driven AI process improvement	"…if you can make that process go faster, again, the bigger guys on Ethos got to a point where they had standardized templates for companies. People must fill this information through and then we compile. So again, I think from a reporting perspective, getting to answers quicker and analysis. I think it would be powerful."	Obj-5	Interview quote
P9	6	Governance and localisation	Secure, provenance-focused adoption	"Well first we need secure and like context-aware models so that it can be tuned to South African law and market signals,	Obj-5	Interview quote

				because if the model respects provenance and variance checks only then analysts will be able to trust it more…. I would must add that governance, not hype, must like lead AI adoption to not erode the confidentiality.”		
P10	6	Analyst training and staged adoption	Training on AI failure modes and pilot deployment	“Starting with firm AI policies and analyst training should be worth considering, particularly on failure mode from there it can extend tools such as from sourcing to monitoring and generating scenario……in my view practical pilot wins trust….hands-on coaching makes the tech feel like a partner rather than a threat.”	Obj-5	Interview quote

Appendix 3: List of respondents

Interviewee	Role	PE/VC Experience (Years)
Participant 1	PE Investor/Partner	17
Participant 2	Managing Director VC	5-10

Participant 3	Principal PE	11
Participant 4	Investment Associate	2
Participant 5	Partner	16
Participant 6	PE Investor/ Non Exec Director	15
Participant 7	PE Transactor	10
Participant 8	Private Markets Specialist	10-
Participant 9	Investment Manager VC	8
Participant 10	PE Principal	10+

Appendix 4: Interview Guide

General

1. What is your current role in PE/VC?
2. What is the number of years of experience in PE/VC?
3. What is the number of years of experience specifically in deal selection?
4. How long has your firm been active in South Africa?

Current Deal-Selection Practice

5. Walk me through your typical deal-sourcing and selection process
6. What types of investment do you primarily focus on?
7. Which stages do you personally own or influence?
8. Which criteria (quantitative and qualitative) carry most weight in deal sourcing /selection?

8.1 Typically what size deals would you say are the norm in the industry? Ballpark figure

8.2 What is generally the industry norm in terms of timeframe in closing these deals?

Use of AI Tools

9. What AI-based tool/s do you currently use in deal evaluation?

9.1 How long have you been using these tools?

10. Can you give a concrete example of a deal where an AI tool played a role?

11. What did it result in?

12. In what way has AI influenced your due diligence process?

13. How has it changed your day-to-day workflow?

14. What factors encourage you, your industry to adopt AI?

15. What reservations or challenges have you encountered?

16. Can you recall a situation where you chose not to use an AI tool, and why?

17. Do you see AI replacing human judgment, or see as primarily used as a support tool? Why?

18. How do you balance “gut feel” or founder assessments or any other consideration against an AI-generated valuation or prediction?

19. What gives you confidence and trust an AI model's output?

20. Have you been able to measure or observe changes in deal performance (IRR, ROE, success measures) attributable to AI usage?

21. What pitfalls or false positives/negatives have surfaced?

21.1 Any privacy concerns and confidentiality when using AI tools? How do you ensure your information is secured?

22. In closing, looking ahead 3–5 years, how do you expect AI's role in your deal flow to evolve? What would make you keep using or abandon AI tools? Would you be willing to pay a substantial amount for an AI tool?