A Systematic Literature Review of Data Analytics Methods Used in Global Corporate Investment Strategies

Exploring AI, Big Data, and FinTech Applications in Strategic Financial Decision-Making

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A dissertation submitted to Auckland University of Technology in partial fulfilment of the requirements for the degree of Master of Business

2026

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Abstract

Corporate investment strategies are increasingly enhanced by data analytics methods, including artificial intelligence (AI), machine learning (ML), and big data analytics. These technologies reshape financial decision-making by enabling faster forecasting, more accurate risk assessment, and optimized capital allocation. Across industries and regions, analytics tools also support strategic agility and alignment between data capabilities and business goals. Based on secondary data, this dissertation investigates how data analytics methods enhance global corporate investment strategies, addressing the lack of integrated, cross-sectoral understanding of how analytics capabilities, governance, and ESG (environmental, social, and governance) considerations jointly shape investment decision-making.

A systematic literature review (SLR) was conducted following PRISMA 2020 guidelines and Braun and Clarke's (2019) six-phase reflexive thematic analysis framework. A total of 25 peer-reviewed articles published between 2015 and 2025 were analysed to synthesise interdisciplinary insights across sectors. The review identifies AI/ML, ESG integration, and data governance as critical enablers of corporate investment strategy, highlighting how these technologies shape analytics-driven decision-making. Organisational factors – including leadership commitment, digital infrastructure, cultural readiness, and regulatory alignment – emerged as pivotal success factors, in translating analytics investments into improved risk intelligence, strategic agility, and long-term value creation. Ethical concerns such as algorithmic bias and transparency remain persistent barriers, along with data quality and global regulatory fragmentation.

Based on the literature review, this study proposes an integrated conceptual framework grounded in Dynamic Capabilities Theory (Teece, 2018) and the Strategic Alignment Model (Coltman et al., 2015). The framework is designed for financial leaders, policymakers, and corporate strategists seeking to enhance decision-making through analytics integration. It serves as a practical guide for applying data analytics in complex investment environments by linking technological enablers (AI, ESG, data governance, and FinTech) with strategic outcomes. The framework's uniqueness lies in its holistic, cross-sectoral synthesis of technological, organisational, and ethical dimensions, offering both theoretical and practical contributions to the evolving field of data-driven corporate finance.

This research provides theoretical insights into the strategic value of data analytics and practical guidance for implementing analytics-enabled investment strategies across global corporate contexts.

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List of Abbreviations

The following table provides definitions of key abbreviations and acronyms used throughout this dissertation. These terms are commonly referenced in discussions related to data analytics, investment strategies, and financial technologies. Including this list ensures clarity for readers and enhances the overall readability of the research.

Abbreviation	Definition
AI	Artificial Intelligence
API	Application Programming Interface
BI	Business Intelligence
CSR	Corporate Social Responsibility
DCT	Dynamic Capabilities Theory (Teece, 2018)
ESG	Environmental, Social, and Governance
FinTech	Financial Technology
ML	Machine Learning
OECD	Organisation for Economic Co-operation and Development
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Page et al., 2021)
ROA	Return on Assets
ROI	Return on Investment
SAM	Strategic Alignment Model (Coltman et al., 2015)
SLR	Systematic Literature Review
SMEs	Small and Medium Enterprises
VC	Venture Capital

Note: All abbreviations listed above will be used consistently throughout this dissertation.

Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Signature: 

Date: *27th January 2026 (27/01/2026)*

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Dr. Ranjan Vaidya, for his invaluable guidance, support, and encouragement throughout this research journey. Dr. Vaidya's expertise and constructive feedback were instrumental in shaping the direction and quality of this dissertation.

I am also grateful to the academic and library staff at Auckland University of Technology for providing essential resources and support that enabled the completion of this systematic literature review.

Finally, I extend my heartfelt thanks to my family and friends for their patience, motivation, and unwavering support during my postgraduate studies.

Ethics Approval

This research involved a systematic literature review of published academic sources only. No human participants, personal data, or observational data were collected. Therefore, AUT Ethics Committee approval was not required for this study.

Chapter 1: Introduction

1.1 Introduction: Big Data Analytics and Corporate Investment Strategies

The integration of data analytics into corporate investment strategies has enabled businesses to navigate complex financial environments with greater precision. In today's corporate landscape, data analytics has emerged as a fundamental driver of strategic planning, risk management, and operational efficiencies (Ahmed, Shaheen, & Philbin, 2022; Tiwari, 2024). For example, the OECD Economic Outlook (OECD Economics Department, 2025) highlights the increasing role of macroeconomic analytics in shaping corporate investment decisions. By leveraging big data analytics, firms can enhance forecasting accuracy and improve strategic investment planning. This aligns with the growing recognition that data-driven insights offer a competitive advantage in global markets. Furthermore, AI advancements in capital market activities, illustrate how machine learning models are refining financial decision-making, offering firms an unprecedented level of precision in investment planning (Abbas et al. 2024).

The rapid advancement of machine learning, artificial intelligence, and predictive analytics further underscores the significance of data analytics in investment strategies. Traditional investment models, which often relied on historical data and expert judgment, have proven to be less agile and accurate compared to modern analytical methods (Mikalef, Pappas, Krogstie, & Pavlou, 2020; Buczynski, Cuzzolin, & Sahakian, 2021). With the proliferation of financial technologies, companies now have the capability to harness real-time data, enabling them to make more informed investment decisions, optimize asset allocation, and mitigate risks more effectively (Ghasemaghaei, 2019; Mikalef et al., 2020).

A key advantage of data analytics is its ability to support decision-making in uncertain or volatile environments. This is particularly important for global firms operating across multiple jurisdictions, where geopolitical shifts, currency fluctuations, and regulatory diversity can complicate traditional investment forecasting methods. Analytics platforms allow these firms to consolidate internal and external data sources – ranging from financial statements to social media sentiment – to gain a holistic view of investment risk and opportunity (Chen, Liu, & Liu, 2018; In et al., 2019). This capability is not only improving the speed of corporate decision-making but also increasing the reliability of those decisions under time constraints. Despite these advancements, organisations continue to struggle with translating analytics capabilities into consistently effective, ethical, and strategically aligned investment decisions, particularly across global and cross-sectoral contexts.

Moreover, data analytics enhances investor confidence by providing transparency and traceability in investment decisions. By quantifying uncertainties and identifying patterns that may not be immediately evident through conventional analysis, firms can demonstrate a more structured and systematic approach to portfolio management. In turn, this strengthens investor trust and promotes more stable capital inflows, especially in markets with heightened volatility or limited regulatory maturity (Boubaker et al., 2023). Such transparency is especially vital in the context of ESG (environmental, social, and governance) investing, where data analytics is increasingly used to monitor sustainability metrics, identify ethical violations, and track long-term non-financial performance indicators (Lim, 2024; Wang et al., 2024).

The transformation of corporate finance via big data analytics is exemplified by its impact on strategic investment decisions. Scholars have shown that analytics-driven strategies facilitate more accurate predictions and enable organizations to make data-backed decisions that align with their long-term financial goals (Aderemi et al., 2024; Aro, 2024). As firms continue to invest in big data technologies, there is evidence to suggest that these investments directly contribute to higher returns on investment and enhanced operational efficiency, as evidenced by the growing adoption of predictive models in sectors such as wealth management (Banerjee et al., 2022; Petersone et al., 2022). Furthermore, the integration of big data with other emerging technologies like artificial intelligence (AI) and machine learning is reshaping the landscape of corporate investment strategies, offering new avenues for enhancing both the precision and the scalability of decision-making processes (Liu, Zhang, & Zhang, 2024).

The increasing availability of big data and advanced analytical tools has transformed how organizations approach investment, shifting from intuition-based decision-making to data-driven methodologies (Alsmadi et al., 2023). This transformation is particularly evident in industries that rely heavily on data-driven insights – such as energy, logistics, healthcare, and telecommunications – where strategic investments must be justified with robust, real-time analytics to ensure operational alignment and fiscal responsibility (Boubaker et al., 2023; Liu, Zhang, & Zhang, 2024). As data ecosystems mature, these sectors increasingly rely on predictive and prescriptive models to support high-stakes capital allocation decisions (Ghasemaghaei, 2019). Moreover, as stakeholder expectations continue to rise, corporate investment teams are under mounting pressure to demonstrate transparency, sustainability alignment, and return predictability – an evolution driven by both internal strategic mandates and external regulatory demands (Cowgill et al., 2020; Lim, 2024; Wang et al., 2024). In this context, data analytics serves not only as a tool for competitive advantage but also as a compliance mechanism and trust-building instrument, enabling organizations to meet ESG benchmarks and investor accountability standards (Adeyelu, Ugochukwu, & Shonibare, 2024; OECD Economics Department, 2025). These concerns highlight the need for a comprehensive understanding of both the opportunities and constraints

associated with analytics-driven decision-making, especially within the context of global market dynamics (Raguseo & Vitari, 2018). Despite this growing body of research, there remains limited consensus regarding how data analytics is strategically integrated into corporate investment decision-making, particularly when governance and ESG considerations are taken into account, highlighting the absence of a cohesive synthesis across these domains.

1.2 Big Data Adaption Challenges and Research Gap

Despite its many advantages, the adoption of big data analytics in corporate investment strategies presents several challenges. The first challenge concerns the integration of large-scale data solutions within existing corporate structures, which often creates significant technical and organisational barriers (Oncioiu et al., 2019; Çınar, 2024). The second challenge relates to data security, regulatory compliance, and ethical considerations, which continue to complicate the implementation of analytics-driven decision-making frameworks in corporate finance (Schnegg & Möller, 2022; Al-Okaily & Al-Okaily, 2024). The third challenge involves the risks associated with biased decision-making and privacy issues – while big data expands financial services, these risks often remain insufficiently addressed in practical and regulatory contexts (Abraham, Schmukler, & Tessada, 2019). Moreover, the absence of responsible data use, transparent algorithm design, and consistent regulatory oversight prevents the development of trust in AI-powered investment tools (Cowgill et al., 2020; Adeyelu, Ugochukwu, & Shonibare, 2024). Collectively, these challenges underscore the need for a structured framework that balances technological innovation with ethical governance, ensuring responsible and effective use of analytics in corporate investment strategy.

Building on these challenges, several research gaps can be identified in the existing literature. The first gap is the limited scope of prior systematic literature reviews (SLRs), which have often focused narrowly on technological adoption or organisational capabilities in isolation (Mikalef et al., 2020; Snyder, 2019). The second gap is the lack of a holistic synthesis that integrates ESG, ethical AI governance, and macroeconomic analytics into the broader discussion of strategic investment decision-making (Boubaker, Liu, & Mu, 2023; Adeyelu et al., 2024). The third gap concerns the absence of a global and cross-sectoral perspective – most studies examine individual industries or specific technologies rather than exploring the broader strategic implications across multiple contexts (Conboy et al., 2020; Abbas et al., 2024). The fourth gap involves the limited exploration of emerging data sources, such as social media analytics, in shaping predictive investment models and corporate foresight (Chen, Liu, & Liu, 2018; In et al., 2019).

While existing studies provide valuable insights into analytics adoption and investment decision-making, this body of literature remains conceptually fragmented and strategically under-theorised. In particular, the separation of analytics capability discussions from governance and ESG considerations limits the explanatory power of current models.

This dissertation addresses these gaps by conducting a systematic literature review (SLR) that (1) synthesises technological, organisational, and governance perspectives, (2) integrates ESG and ethical AI considerations into investment strategy analysis, and (3) adopts a global, cross-sectoral lens to capture broader strategic implications. Through this review, five dominant influencers are identified – strategic enablers, ESG integration, ethical governance, AI/FinTech capabilities, and regulatory alignment – which collectively shape analytics-enabled corporate investment decision-making. The study uniquely contributes to the literature by developing an integrated conceptual framework that synthesises the roles of ESG considerations, advanced analytics and AI capabilities, governance mechanisms, and macro-regulatory factors in shaping contemporary corporate investment strategies.

Finally, this study also bridges the gap between academic theory and practical application. While many firms have invested in analytics capabilities, evidence suggests that technical adoption alone does not ensure strategic value creation. Organisational culture, leadership commitment, data governance, and employee capability remain pivotal enablers of success (Mikalef et al., 2020; Brynjolfsson & McElheran, 2019). Accordingly, this dissertation not only examines the technological aspects of investment analytics but also highlights the organisational and contextual factors that determine their effectiveness. By addressing all the identified gaps, this research contributes to a more comprehensive understanding of how data analytics enhances global corporate investment strategies.

1.3 Research Aim, Question and Objectives

This study is guided by the central research question: "*How can data analytics methods enhance global corporate investment strategies?*"

To address this question, the dissertation conducts a systematic literature review. The objectives of this research are to:

1. Systematically review existing literature on the application of data analytics in corporate investment strategies.
2. Identify key technological, organisational, ethical, and regulatory enablers and barriers influencing analytics-enabled investment decision-making.

3. Synthesise insights across sectors to develop an integrated conceptual framework linking analytics capabilities to strategic investment outcomes.

Together, this research question and its associated objectives aim to clarify the strategic mechanisms through which data analytics influences corporate investment decision-making, addressing fragmentation within the existing literature.

By synthesizing existing research and industry case studies, this study will provide a comprehensive analysis of how data analytics influences corporate investment strategies. The findings will contribute to the growing body of academic work on data-driven investment strategies while offering practical insights for organizations seeking to optimize their investment frameworks through advanced analytics. This research is especially valuable for firms operating in rapidly evolving or data-intensive environments, such as technology, finance, logistics, and energy sectors.

The uniqueness of this study lies in its systematic methodology and global scope. By conducting an SLR, the research follows a transparent, replicable approach to gather and interpret high-quality academic literature. As noted by Snyder (2019), systematic reviews help eliminate selection bias and provide a structured means of identifying thematic patterns across disciplines. This study draws upon a wide range of scholarly contributions, including peer-reviewed journal articles, industry whitepapers, and institutional reports, ensuring a multi-faceted view of analytics in investment contexts.

1.4 Structure of the Dissertation

This dissertation is organised into six chapters:

- **Chapter 1: Introduction** – Establishes the research background, outlines the research problem, and presents the research question and objectives. It also justifies the study's significance within the context of global data-driven investment strategy.
- **Chapter 2: Research Design and Methodology** – Details the systematic literature review (SLR) methodology, including the use of PRISMA guidelines (Page et al., 2021), thematic analysis (Braun & Clarke, 2019), and the inclusion/exclusion criteria that guide data selection. A thematic model was developed to integrate findings across domains such as ESG, AI, and data ethics, providing a structured lens for understanding the strategic application of analytics in corporate investment decisions. This framework is theoretically grounded in Dynamic Capabilities Theory (Teece, 2018) and the Strategic Alignment Model

(Coltman et al., 2015), both of which underscore the importance of aligning digital capabilities with long-term organisational strategy (see Figure 4 in Chapter 5).

- **Chapter 3: Literature Review** – Synthesises current academic and industry research on big data, AI, FinTech, ESG, and digital transformation as they relate to corporate investment strategies (Ghasemaghaei, 2019; Mikalef et al., 2020).
- **Chapter 4: Findings** – Presents the results of the thematic analysis, including theme frequency, strategic relevance across sectors, and conceptual patterns derived from the reviewed literature.
- **Chapter 5: Discussion** – Interprets the findings through the lens of Dynamic Capabilities Theory (Teece, 2018) and the Strategic Alignment Model (Coltman et al., 2015), and links them to broader theoretical, ethical, and strategic implications.
- **Chapter 6: Conclusion** – Summarises the research contributions, highlights theoretical and practical implications, outlines limitations, and proposes directions for future academic and industry research.

In summary, this chapter has established the background, rationale, and significance of exploring how data analytics methods enhance global corporate investment strategies. This dissertation addresses this central question by identifying the key enablers and barriers to data analytics adoption across sectors. The following chapter outlines the systematic literature review methodology used to investigate this question and guide the thematic synthesis presented in later chapters.

Chapter 2: Research Methodology

2.1 Chapter Overview

This chapter outlines the research methodology adopted to address the central research question. A systematic literature review (SLR) was employed to ensure transparency, rigour, and replicability, following best-practice guidance from Snyder (2019), Gusenbauer and Haddaway (2020), and the PRISMA 2020 protocol (Page et al., 2021). A systematic literature review is particularly suited to emerging interdisciplinary topics such as data analytics, where conceptual boundaries are fluid and application varies widely across sectors (Tambe, 2014; Mikalef et al., 2020). This method allows for the structured analysis of diverse, cross-sectoral literature in a transparent and replicable manner (Xiao & Watson, 2017; Snyder, 2019).

The chapter follows established qualitative research structures (Creswell & Poth, 2018), outlining the rationale for using an SLR, search strategy, inclusion and exclusion criteria, bias mitigation procedures, data extraction, and Braun and Clarke's (2019) six-phase thematic analysis. Thematic analysis enabled the inductive development of themes to answer the research question. Together, these methodological steps provide a foundation for synthesising peer-reviewed literature on data analytics in the context of corporate investment strategy.

Importantly, this review moves beyond descriptive aggregation of prior findings by adopting a critical and evaluative synthesis approach. Rather than treating existing studies as homogenous or consensus-driven, the analysis explicitly examines areas of convergence, divergence, and contextual limitation across the literature. This approach enables the identification of competing perspectives, conditional outcomes, and underexplored tensions that shape how data analytics influences corporate investment decision-making across organisational and regulatory contexts.

2.1.1 Research Paradigm

This study adopts a qualitative interpretivist paradigm, aligning with the nature of systematic literature reviews aimed at exploring meaning, thematic patterns, and contextual interpretation (Pretorius, 2024; Creswell & Poth, 2018). Pretorius (2024) highlights the centrality of ontology, epistemology, and axiology in shaping interpretivist research, reinforcing the value of reflexivity and researcher-context alignment in knowledge generation.

A qualitative worldview enables a flexible and reflexive analysis of academic texts, consistent with Braun and Clarke's (2019) reflexive thematic analysis framework, which was

applied in this review. This paradigm is particularly suitable for research questions that explore how, why, and in what ways data analytics contribute to corporate investment strategies, rather than seeking quantifiable causal relationships (Snyder, 2019).

Furthermore, systematic reviews grounded in interpretivism emphasise the importance of context, emerging themes, and researcher reflexivity – essential elements for analysing complex, interdisciplinary fields like AI, ESG, and financial technologies (Nowell et al., 2017; Xiao & Watson, 2017). The chosen paradigm supports the goal of this study to synthesise diverse perspectives into a coherent framework for strategic investment analysis.

2.2 Justification for Systematic Literature Review (SLR) Methodology

A systematic literature review (SLR) was selected for this study to provide a comprehensive synthesis of existing research on data analytics methods in corporate investment strategies. The use of an SLR directly supports the central research question by enabling a transparent and replicable process to identify, evaluate, and integrate evidence from diverse academic sources (Snyder, 2019; Page et al., 2021).

SLRs facilitate the integration of findings from multiple studies, allowing for a more generalisable and holistic understanding of complex topics (P S et al., 2024). This approach ensures that insights from various disciplines are systematically examined, making it particularly useful for interdisciplinary research such as data analytics in investment decision-making (Snyder, 2019). Additionally, SLRs help identify gaps in the literature and highlight methodological trends, offering valuable direction for future research (Paul & Criado, 2020). By aggregating knowledge from diverse sources, SLRs contribute to a robust and objective understanding of the subject matter.

While meta-analyses are valuable for quantitative synthesis (Paul & Criado, 2020) and scoping reviews are suited for mapping broad topic areas (Munn et al., 2018), a systematic literature review was selected for its ability to balance depth and breadth while ensuring methodological transparency. Furthermore, the SLR enables critical appraisal and synthesis of findings, which aligns with this study's objective to explore how data analytics methods can enhance corporate investment strategies and to identify thematic patterns that explain their strategic application across global contexts (Snyder, 2019; P S et al., 2024).

In contrast to prior reviews that emphasise descriptive mapping of themes, this study explicitly prioritises critical comparison and interpretive integration across studies. This includes evaluating the conditions under which analytics-driven investment strategies succeed or fail, as

well as assessing the relative influence of governance, ESG, and organisational readiness. Such an approach aligns with High-level qualitative synthesis practices recommended by Snyder (2019) and Braun and Clarke (2019).

The SLR approach adopted here is intentionally designed to capture both thematic depth and interdisciplinary breadth – particularly around emerging themes such as algorithmic ethics, ESG integration, and regulatory harmonisation. This enhances the originality and relevance of the synthesis beyond what prior SLRs have offered (Snyder, 2019). In doing so, this study not only synthesises existing knowledge but also extends prior SLR applications by aligning cross-cutting strategic themes with contemporary corporate finance contexts relevant to modern investment decision-making – a departure from earlier studies that focused primarily on IT capabilities or siloed analytics adoption (Mikalef et al., 2020; Snyder, 2019).

The research process followed a structured, transparent, and replicable SLR approach based on methodological guidance from Snyder (2019), Braun and Clarke (2019), and the PRISMA 2020 framework (Page et al., 2021). The steps undertaken are summarised in Table 1 below.

SLR Stage	Description	Source(s)
Define Research Question	Establish research aim, scope, and guiding question	Xiao & Watson (2017)
Design Search Strategy	Select databases, keywords, Boolean logic, and filters	Page et al. (2021)
Apply Inclusion/Exclusion	Use predefined criteria to screen studies	Braun & Clarke (2019); Snyder (2019)
Extract Data	Extract and code relevant data from included studies	Xiao & Watson (2019); P S et al. (2024)
Thematic Analysis	Apply thematic analysis to synthesise findings	Braun & Clarke (2019)
Quality/Validity Check	Address bias and validate data interpretation through iterative coding and transparency steps	Page et al. (2021); Munn et al. (2018)

Table 1: Summary of Systematic Literature Review (SLR) Steps[1]

This study deliberately adopts a qualitative systematic literature review design to enable theory-informed conceptual integration across a fragmented and interdisciplinary body of research. As Snyder (2019) notes, such reviews are particularly valuable in emerging domains where empirical findings are dispersed across disciplines and lack cumulative coherence. By prioritising synthesis over empirical testing, this approach provides a consolidated analytical foundation upon which future hypothesis-driven and empirical research can build.

[1] Adapted from Snyder (2019), Xiao and Watson (2019), Braun and Clarke (2019), Page et al. (2021), and Munn et al. (2018).

The inclusion of studies spanning diverse sectors and geographic contexts further strengthens the analytical contribution of this review. Such heterogeneity allows for the identification of cross-contextual patterns and higher-order thematic insights, transforming what might traditionally be viewed as a limitation into a methodological advantage. This aligns with Braun and Clarke's (2019) guidance on qualitative synthesis, highlighting that diversity within the included studies supports robust conceptual development rather than narrow empirical generalisation. Together, the qualitative SLR approach and the deliberate inclusion of heterogeneous studies enhance the originality, relevance, and theoretical depth of this research, positioning it to offer meaningful contributions to both academic understanding and practical application in global corporate investment strategies.

The study intentionally employs theory-informed descriptive synthesis as a methodological foundation for analytical integration. Braun and Clarke (2019) emphasise that descriptive depth is essential in qualitative reviews to establish shared conceptual ground prior to higher-level interpretation, particularly in rapidly evolving and interdisciplinary research fields such as analytics-enabled corporate investment. By prioritising descriptive synthesis, this review ensures that emergent themes are meaningfully grounded in the data, supporting both analytical rigor and theoretical coherence.

2.3 Steps in Implementing SLR

To ensure a methodologically rigorous review, this study follows a structured, step-by-step process for implementing the systematic literature review (SLR). Each stage was designed to enhance transparency, consistency, and alignment with the central research question. The detailed stages of the SLR process, including screening, eligibility, and synthesis procedures, are summarised in Tables 1 and 2.

1. **Defining Inclusion and Exclusion Criteria:** Studies were required to explicitly focus on the intersection of data analytics and corporate investment strategies. This ensured that only relevant and methodologically sound research was included, reducing the risk of bias and enhancing reliability.
2. **Comprehensive Literature Search:** A thorough search was conducted across multiple academic databases, including Google Scholar, Scopus, ScienceDirect, and Springer, as well as specialised databases such as ABI/INFORM Collection and Business Source Premier. The full search string and database-specific query strategy are provided in Appendix B. This approach aligns with recommendations from Aderemi et al. (2024) and Mikalef, Boura, Lekakos, and Krogstie (2019), who emphasise the importance of drawing from diverse academic sources for a holistic review. The effectiveness of academic search

systems in systematic reviews is further supported by Gusenbauer and Haddaway (2020), who evaluate the retrieval quality of major databases.

3. **Reviewing the Quality of Studies:** The quality of selected studies was assessed based on methodological rigour and alignment with the research question, as suggested by Ghasemaghaei (2019). Study quality was assessed based on three criteria: publication in peer-reviewed academic journals or conference proceedings, methodological rigour in the research design, and relevance to the study's focus on data analytics applications in corporate investment strategies. This ensured that only high-quality and contextually relevant research was incorporated into the review.
4. **Categorising Findings into Thematic Areas:** Key themes related to corporate investment strategies and data analytics methods were identified. This thematic categorisation highlighted emerging trends, challenges, and knowledge gaps, consistent with the analytical approaches of Farooq et al. (2022) and Mikalef et al. (2019). This structured classification enhanced the study's analytical depth, enabling a comprehensive synthesis of the literature in alignment with the central research question.

This study adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency, replicability, and systematic documentation of the review process, following best practices outlined by Page et al. (2021) and Wijaya et al. (2024). The review process followed the PRISMA framework (Page et al., 2021), as visualised in Appendix A. The PRISMA framework is instrumental in maintaining methodological rigour and allows for enhanced comparability with previous systematic reviews in the field.

2.3.1 SLR Framework Mapping

To enhance the transparency and reproducibility of the systematic literature review process, this study adopted the eight-step structure proposed by Xiao and Watson (2017), which is widely used in information systems research. Table 2 provides an overview of how each step was applied in this study.

SLR Step	Based on (Xiao & Watson, 2017)	Application in This Dissertation
1. Articulating the Research Question	Defining the focus of the review clearly	Framed around: *How can data analytics methods enhance global corporate investment strategies?*
2. Creating and Justifying the Review Protocol	Planning the review method, sources, and criteria	Defined SLR methodology, databases, inclusion/exclusion criteria
3. Conducting the Literature Search	Executing database searches using keywords and Boolean logic	Searched Scopus, ScienceDirect, Google Scholar, ABI/Inform, etc.

4. Screening for Inclusion	Applying criteria to include/exclude sources	Applied date range (2015–2025), peer-reviewed only, English-language studies
5. Assessing Study Quality	Ensuring methodological rigor	Prioritized empirical, peer-reviewed studies; excluded low-quality or non-relevant ones
6. Extracting Data	Collecting key variables from selected studies	Used Excel matrix to track author, year, methods, findings, and context
7. Synthesizing Findings	Grouping and analyzing data thematically	Applied Braun & Clarke's (2019) thematic analysis approach
8. Reporting Results	Structuring findings clearly	The identified themes are described in Chapter 3. The findings from the study are presented in Chapter 4. The findings and their implications are discussed in Chapter 5

Table 2: Systematic Literature Review Process

2.4 Identification of Literature

2.4.1 Scope of Studies Reviewed

Unlike some prior systematic reviews that segmented findings by industry, this study adopted a cross-sectoral approach. The 25 screened studies were selected for their relevance to corporate investment strategy and data analytics, regardless of specific industry context. This broader thematic orientation allows the synthesis of universally applicable insights, especially in light of the increasing convergence in how analytics technologies are deployed across sectors (Snyder, 2019; Ahmed, Shaheen, & Philbin, 2022).

This study adopts a cross-sectoral synthesis approach rather than an industry-specific one, enabling greater generalisability of insights across organisational contexts. Such an approach is consistent with Snyder's (2019) argument that systematic literature reviews benefit from broader thematic framing when examining interdisciplinary domains such as data analytics. Cross-sectoral reviews allow for the identification of common success factors and challenges in data-driven investment strategies regardless of sectoral differences, thereby ensuring more versatile theoretical and practical applications (Mikalef et al., 2020; Ahmed et al., 2022).

This methodological stance also ensures that the conceptual framework developed in Chapter 5 reflects strategic, rather than industry-specific, priorities. It aligns with the methodological flexibility recommended for thematic synthesis in systematic literature reviews (Braun & Clarke, 2019; Xiao & Watson, 2017).

2.4.2 Search Terms

The systematic review process in this study followed established protocols for transparency and replicability. In line with Gusenbauer and Haddaway (2020), search strategies were optimized for both precision and recall across multiple academic databases, including Scopus, Google Scholar, and ScienceDirect. Boolean operators were used to refine search terms, as recommended by Fan et al. (2015), to maximize relevance. To ensure methodological robustness, the study adhered to the PRISMA 2020 guidelines, which facilitate the transparent selection and exclusion of studies through a structured flow diagram (Page et al., 2021). This process aligns with Snyder's (2019) guidance on designing structured literature reviews in interdisciplinary fields such as business and data analytics.

The literature search was conducted across several academic databases to ensure comprehensive coverage of relevant studies. These included Google Scholar, Scopus, ScienceDirect, ABI/INFORM Collection, and Business Source Premier. Records were also identified through cross-referencing and conference proceedings to capture additional relevant research that may not have appeared in the initial database search. Following duplicate removal and screening procedures, a total of twenty-five studies were retained for further analysis, as illustrated in the PRISMA flow diagram presented in Section 2.7.

The literature search utilised targeted keywords to capture the intersection of data analytics and corporate investment, including:

- "Corporate investment strategies"
- "Data analytics in investment"
- "Big data investment decisions"
- "Machine learning for investment"
- "Financial data analytics"
- "Portfolio optimization with AI"
- "Predictive analytics in finance"
- "Corporate investment decision-making"
- "Data-driven investment strategies"
- "Big data in corporate finance"
- "Machine learning in financial forecasting"
- "Deep learning for stock market prediction"
- "AI-driven portfolio management"
- "Quantitative investment strategies with data analytics"
- "Big data analytics in financial markets"

Boolean operators (AND, OR) were used to refine search queries across databases, following strategies recommended by Fan et al. (2015). To ensure comprehensive coverage, search strategies were iteratively refined by testing different keyword combinations and assessing retrieval effectiveness.

2.5 Risk of Bias and Mitigation Strategies

Despite its methodological rigor, systematic literature reviews (SLRs) are susceptible to various forms of bias, necessitating mitigation strategies to ensure credibility. One key concern is publication bias, where reliance on only high-impact journal outlets may overlook valuable insights available in other academic sources (Siddaway et al., 2019). To minimise this risk, the review deliberately included both peer-reviewed journal articles and conference papers, providing a broader representation of contemporary scholarship and methodological diversity (Farooq et al., 2022; Velte, 2022).

Selection bias is another potential limitation, which can arise from the subjective inclusion or exclusion of studies. To address this, the PRISMA 2020 framework (described in section 2.8) was applied to provide transparency and reproducibility across the identification, screening, eligibility, and inclusion stages (Page et al., 2021). In addition, researcher bias was mitigated through a manual coding process, where patterns were identified and grouped systematically in Excel rather than through automated software. This ensured close engagement with the material and reflexive consideration of emerging concepts (Azarian et al., 2023).

Collectively, these measures strengthen the reliability and validity of the review, while also aligning with best-practice standards for systematic synthesis in management and information systems research.

2.6 Inclusion and Exclusion Criteria

2.6.1 Inclusion Criteria

The inclusion criteria for this study were designed to ensure both relevance and methodological rigour. First, only peer-reviewed journal articles and conference papers published from 2015 onward were considered. This time frame was selected to align with recommendations by Farooq et al. (2022), who emphasise the importance of focusing on contemporary research to capture recent methodological and technological developments. Second, the studies were required

to explicitly address applications of data analytics within corporate investment contexts, ensuring a direct connection to the research objectives. Third, only papers published in English were included to maintain consistency in quality and accessibility of interpretation (Velte, 2022). Finally, research that examined global investment strategies with cross-sectoral or broad industry applicability was prioritised, given the study's focus on identifying generalisable patterns across corporate contexts. While the systematic review focused primarily on peer-reviewed journal articles and conference papers for the core analytical dataset, a limited number of institutional and policy reports (e.g., publications from organisations such as the Organisation for Economic Co-operation and Development, the World Economic Forum, and the Financial Industry Regulatory Authority) were consulted to provide contextual insights into global financial trends and regulatory developments.

2.6.2 Exclusion Criteria

To maintain clarity of scope, several types of studies were excluded. Research that lacked explicit discussion of data analytics in investment decision-making was removed, as it did not contribute directly to the research question (Snyder, 2019). In addition, non-academic sources such as blogs, opinion pieces, and white papers were excluded to ensure that the analysis remained grounded in peer-reviewed scholarship. Similarly, studies focusing exclusively on personal or retail investment strategies were excluded, as these diverge from the corporate investment perspective central to this dissertation (Snyder, 2019). The screening and selection outcomes are summarised in the PRISMA 2020 flow diagram (Figure 1, see Section 2.7), which details how the final set of studies was identified and included in this review (Page et al., 2021).

2.7 PRISMA Flow Diagram

Following the application of the inclusion and exclusion criteria outlined above, the study selection process was documented using the PRISMA 2020 framework (Page et al., 2021), as shown in Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) is a widely recognised framework that enhances transparency and reproducibility in systematic reviews by standardising how studies are identified, screened, and reported (Page et al., 2021). Its emphasis on methodological transparency makes it particularly relevant for management and information systems research, where rigorous review processes are essential for credibility (Farooq et al., 2022).

The following PRISMA 2020 flow diagram (Figure 1) visually represents the systematic literature review (SLR) process undertaken in this study (Page et al., 2021). It outlines each stage

of the review, illustrating how records were identified, screened, assessed for eligibility, and ultimately included in the final synthesis.

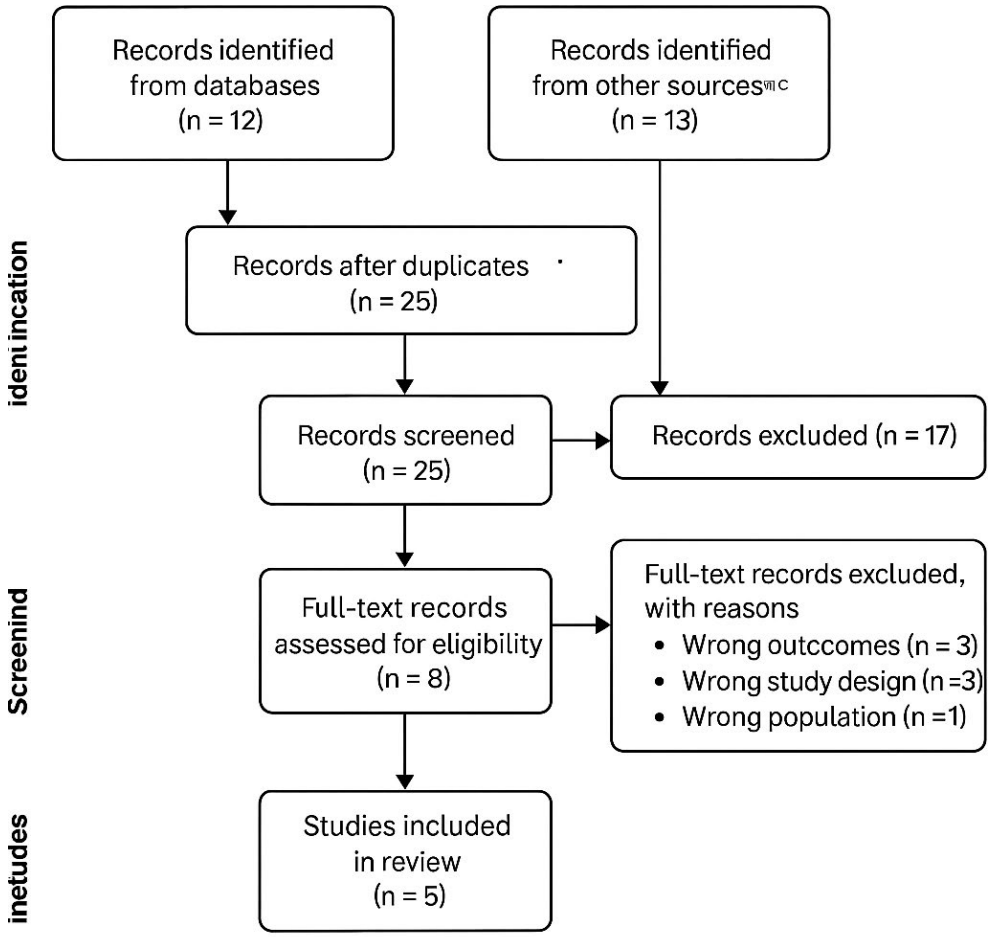

Figure 1: PRISMA Flow Diagram of Study Selection

Note. Adapted from Page et al. (2021). Figures correspond exactly to the review stages described in the text.

As shown in Figure 1, the initial database search identified 12 records, and an additional 13 records were found through other sources such as conference proceedings and cross-references. After removing duplicates, 25 records remained and were screened for relevance based on titles and abstracts. Of these, 17 records were excluded for not meeting the inclusion criteria. The remaining **eight** full-text articles were then assessed for eligibility. Following detailed review, **seven** studies were excluded due to wrong outcomes (n = 3), inappropriate study design (n = 3), or mismatched population (n = 1). Ultimately, **five** studies met all inclusion criteria and were incorporated into the final review. The 25 studies were coded during preliminary thematic analysis to identify patterns and emerging concepts. The 5 studies that satisfied all eligibility criteria served as the core evidence base for the final qualitative synthesis.

Single-reviewer screening was conducted consistently using the predefined inclusion and exclusion criteria. To reduce potential selection bias and enhance procedural consistency, all records were rechecked against the eligibility criteria during both the **title-abstract screening stage** and the **full-text review stage**. This iterative verification process ensured that study selection remained aligned with the methodological parameters established for the systematic literature review.

While the PRISMA process identified five studies that fully met the strict eligibility criteria for detailed qualitative synthesis, the broader set of twenty-five studies identified during the screening stage were also coded and examined at a preliminary analytical level. These studies contributed to the identification of recurring concepts, contextual insights, and emerging thematic patterns within the literature.

The five studies retained after the final PRISMA eligibility assessment therefore served as the core evidence base for deeper interpretive synthesis, while the wider corpus of twenty-five screened studies provided contextual support and thematic triangulation during the coding process.

Importantly, this detailed PRISMA record-keeping is not a limitation but a **methodological strength**. By following the PRISMA 2020 guidelines, this study ensures transparency, rigor, and reproducibility in the identification, screening, and inclusion of studies. While twenty-five studies were screened and coded during the thematic analysis process, five studies ultimately satisfied all eligibility criteria for inclusion in the final qualitative synthesis (Page et al., 2021; Braun & Clarke, 2019). This demonstrates that the reported numbers reflect careful analytical abstraction rather than inconsistency, positioning PRISMA as a credibility anchor rather than a liability.

This process, as summarised in the PRISMA 2020 flow diagram above, further enhances the transparency and reproducibility of the systematic review. It demonstrates how the literature was systematically narrowed from an initial pool of 25 screened studies to 5 high-quality articles included in the qualitative synthesis. This distinction between the screened study corpus and the final synthesis set is consistent with systematic literature review practices, where broader screening pools often support contextual understanding and thematic exploration while a smaller subset forms the core evidential basis for detailed qualitative synthesis.

As this study forms part of a Master’s dissertation conducted by a single researcher, the screening and selection process was undertaken by one reviewer. To minimise potential bias, the predefined inclusion and exclusion criteria were applied consistently across all records, and articles were rechecked at multiple stages of the screening process to ensure alignment with the

study's research objectives. This approach reflects methodological practices commonly adopted in graduate-level systematic literature reviews.

2.8 Data Extraction Process

A structured data extraction process systematically recorded key details from each study, including authorship, publication year, methodologies, data analytics techniques, and key findings. This aligns with the approach detailed by Raguseo and Vitari (2018), ensuring the accurate capture of essential insights. Extracted data was stored in a standardized coding framework to facilitate systematic analysis. To enhance reliability, an initial pilot extraction was conducted using a small sample of studies. This iterative approach, as recommended by Maroufkhani et al. (2019), refined the extraction framework to minimize bias and improve consistency. The extracted data underwent a secondary review process to ensure completeness and accuracy.

2.9 Contextual Considerations in Investment Strategy Analysis

While this study followed an SLR methodology, it recognized the broader economic and technological contexts influencing corporate investment strategies. To provide macroeconomic insights, authoritative sources such as the OECD Economic Outlook (OECD, 2024a) were referenced, highlighting global economic conditions impacting investment decisions. Additionally, the OECD Digital Economy Outlook (OECD, 2024b) informed the discussion on digital transformation's role in corporate investment frameworks. These sources did not form part of the core dataset but offered valuable contextual insights for thematic analysis.

2.10 Data Analysis Method (Thematic Analysis)

This study applies thematic analysis as described by Braun and Clarke (2019), a widely adopted qualitative analysis method known for its systematic yet flexible approach to identifying and interpreting patterns in textual data. The process followed their six-phase model, which enables rigorous, transparent, and replicable coding within a literature-based dataset.

The coding was conducted in Microsoft Excel, where each article was broken down into analytical segments across author, publication year, domain, and keywords. These excerpts were manually coded in iterative rounds. During Phase 1 (familiarisation), articles were read repeatedly. Phase 2 (initial coding) involved generating short descriptors. In Phases 3 and 4, related codes were collated into preliminary themes, refined for coherence, and grouped into higher-order

categories. The process continued through theme review, definition, and final write-up (Phases 5 and 6), consistent with the six-phase framework outlined by Braun and Clarke (2019).

Beyond identifying recurring themes, the thematic analysis was used to interrogate relationships, tensions, and hierarchies between concepts identified in the literature. This enabled the study to distinguish between dominant assumptions, contested findings, and context-dependent outcomes across studies, thereby supporting a more critical and theory-informed synthesis rather than a purely descriptive thematic summary.

To enhance transparency, an example of the Excel spreadsheet used during coding is provided in **Appendix C**, illustrating how codes were generated, grouped, and refined into thematic categories. This visual representation complements the detailed coding matrix presented in Appendix C and demonstrates the iterative process of theme development used in the thematic analysis. This approach ensures transparency and replicability, aligning with thematic analysis best practices recommended in qualitative systematic reviews (Nowell et al., 2017). A total of 25 articles were coded, with themes grouped across strategic, technical, ethical, and macroeconomic dimensions. Appendix C outlines the full coding matrix.

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The themes generated through this thematic analysis informed the structure of the findings presented in Chapter 4. These themes were subsequently interpreted and integrated to develop the conceptual framework presented in Chapter 5, which illustrates how data analytics capabilities influence corporate investment strategy across organisational contexts.

2.10.1 Thematic Analysis Framework

Thematic analysis is a widely used method for identifying, analysing, and reporting patterns within qualitative data. Unlike more rigid approaches such as systematic coding frameworks that emphasise strict categorisation and theory-building (Farooq et al., 2022; Velte, 2022), thematic analysis offers a flexible and accessible approach to pattern recognition across diverse datasets. It is particularly well-suited for synthesising existing literature, as it enables researchers to systematically identify recurring concepts, organise them into broader themes, and interpret their relevance within a given research context (Braun & Clarke, 2019). This makes thematic analysis especially appropriate for this dissertation, which seeks to consolidate insights from prior studies to

understand how data analytics enhances global corporate investment strategies (Mikalef et al., 2020; Ghasemaghaei, 2019).

To improve clarity and methodological transparency, Table 3 presents the six-phase approach to reflexive thematic analysis as outlined by Braun and Clarke (2019), alongside how each phase was applied in this study.

Phase	Description (Braun & Clarke, 2019)	Application in This Study
Familiarisation with data	Immersing in the data through repeated reading and note-taking	All 25 included studies were read multiple times to capture key insights and preliminary observations.
Generating initial codes	Identifying meaningful and relevant features of the dataset	Open coding was conducted in Microsoft Excel, where key excerpts were coded according to methodological focus, analytics techniques, and strategic investment outcomes.
Searching for themes	Collating codes into potential themes	Related codes were grouped into conceptual clusters, forming preliminary themes such as ESG, AI and analytics capabilities, FinTech infrastructure, and governance.
Reviewing themes	Checking coherence and consistency across themes and the dataset	Themes were refined through iterative comparison across studies, merging overlapping categories and removing weak or redundant themes.
Defining and naming themes	Refining and clearly defining each theme	Final themes were defined and aligned with the study's objective of developing a data-driven corporate investment strategy framework.
Producing the report	Synthesising and presenting findings	The refined themes informed the findings presented in Chapter 4 and the conceptual framework developed in Chapter 5.

Table 3: Application of Braun and Clarke's (2019) Six-Phase Thematic Analysis Framework

Note. Adapted from Braun and Clarke (2019).

Table 3 outlines how Braun and Clarke's (2019) six-phase reflexive thematic analysis framework was operationalised in this study. The structured application of this approach enhanced methodological transparency and analytical rigour during data synthesis.

In the first phase, familiarisation involved an immersive reading of all 25 included studies, allowing the researcher to take initial notes and develop an intuitive sense of the literature landscape (Braun & Clarke, 2019). This was followed by generating initial codes in Phase 2, where recurring concepts and ideas were systematically tagged using an open coding strategy in Microsoft Excel (Braun & Clarke, 2019). This process ensured that salient patterns were captured consistently across the literature (Creswell, 2018).

During Phase 3 (Searching for Themes), these codes were clustered into preliminary theme categories based on conceptual similarity – resulting in broad areas such as ESG and ethical governance, AI and analytics capabilities, FinTech infrastructure, and strategic alignment (Braun & Clarke, 2019). The reviewing themes phase (Phase 4) involved refining the thematic structure by examining the coherence of codes within themes and the distinctiveness between themes (Braun & Clarke, 2019). Redundant or weak themes were eliminated at this stage to maintain clarity and focus (Braun & Clarke, 2019).

Phase 5 (Defining and Naming Themes) was critical in sharpening the conceptual clarity of each thematic category (Braun & Clarke, 2019). Here, themes were linked to their relevance within corporate investment strategy frameworks, aligning closely with the study's aim to build a sector-agnostic yet strategically robust model (Mikalef et al., 2020; Coltman et al., 2015). Finally, Phase 6 (Writing Up) integrated the fully developed themes into Chapter 4, with their conceptual relationships forming the foundation of the integrated framework presented in Chapter 5 (Braun & Clarke, 2019).

The iterative and reflexive nature of this process not only aligns with best practice in qualitative synthesis but also ensures that the findings are grounded in both the data and the broader theoretical positioning of this study (Braun & Clarke, 2019).

2.10.2 Application of Braun & Clarke’s (2019) Six-Phase Framework

The thematic analysis followed the six-phase process proposed by Braun and Clarke (2019), a widely recognised framework for identifying, analysing, and reporting patterns across qualitative data. This iterative and recursive approach ensured both depth and methodological rigour throughout the analysis. The six phases included: (1) data familiarisation, (2) generation of initial codes, (3) theme searching, (4) theme reviewing, (5) theme defining and naming, and (6) report production.

The application of Braun and Clarke’s (2019) six-phase thematic analysis framework in this study is summarised in Table 3 above.

As shown in Table 3, Braun and Clarke’s (2019) six-phase reflexive thematic analysis framework was systematically applied in this study. While coding the data, an inductive approach was used, allowing themes to emerge organically from the reviewed literature rather than being imposed by pre-existing theoretical frameworks (Braun & Clarke, 2019).

For example, Gu, Kelly, and Xiu (2020) examined machine learning methods for empirical asset pricing and noted that predictive models provide improvements in forecasting asset returns. In this study, a statement from their research was initially coded as “AI applications in forecasting.” Through subsequent cycles of coding, this code was merged with similar findings from Liu, Zhang, and Zhang (2024) and Yang and Shen (2025), contributing to the broader theme of *Predictive Analytics and AI Applications*.

The coding process was supported by a structured Excel-based matrix that grouped studies by common conceptual clusters (P S et al., 2024), ensuring consistency and traceability in theme development. Initial codes were refined through multiple cycles of analysis. For instance, early codes related to “regulatory restrictions,” “compliance frameworks,” and “data governance standards” were initially recorded as discrete categories. After iterative review and comparison, these were consolidated into the higher-order theme of *Regulatory and Policy Frameworks*. This refinement enhanced coherence across themes and reduced redundancy.

To ensure credibility and minimise bias, cross-validation was conducted through repeated comparison of thematic groupings against the original studies. This ensured alignment with the study’s research objectives and enhanced the transparency of the analytical process. In addition, reflexivity was maintained throughout the coding and theme development process. The researcher continuously reviewed coding decisions and thematic groupings to ensure that interpretations remained grounded in the source literature rather than being influenced by prior assumptions or expectations (Braun & Clarke, 2019).

Maintaining this reflexive stance strengthened the analytical rigour of the study and ensured that the final thematic framework emerged inductively from the reviewed literature rather than being imposed by pre-existing theoretical models.

2.11 Data Synthesis & Analysis Techniques

To ensure systematic and rigorous synthesis of the reviewed literature, this study employed a structured thematic analysis framework for identifying patterns and extracting key themes. The coding process followed an iterative approach, whereby preliminary themes emerged through initial reading and were refined through repeated cycles of comparison, categorization, and consolidation.

A coding matrix was developed to organise concepts, enabling consistency across themes and enhancing analytical transparency (P S et al., 2024). This approach ensured that the emerging thematic structure was grounded in the reviewed studies while also capturing the contextual

richness of the literature. To minimise subjectivity and strengthen methodological transparency, the thematic coding process was conducted inductively, allowing themes to emerge from the data rather than being imposed by pre-existing theoretical categories (Siddaway et al., 2019).

Through this process, the final thematic structure was both evidence-based and reflective of the complexities inherent in data analytics and investment strategy research. Accordingly, the synthesis presented in Chapter 4 does not assume uniform effects or universal applicability of data analytics in corporate investment contexts. Instead, it critically examines variation across organisational settings, governance environments, and strategic priorities, forming the analytical foundation for the integrated conceptual framework developed in Chapter 5.

Chapter 3: Literature Review – Five Influencers of Data Analytics on Corporate Investment Strategies

3.1 Chapter Overview

This chapter presents a description of the main themes from the literature review, synthesising academic and industry research on data analytics in corporate investment finance (Chen et al., 2018; Mikalef et al., 2020). It draws on empirical studies from 2015 to 2025 and frames the theoretical landscape that supports this dissertation (Åstebro, 2021; Ghasemaghaei, 2019). The literature review explores how advanced analytics tools such as artificial intelligence (AI), machine learning (ML), and financial technology (FinTech) enhance strategic investment decision-making, while also examining issues related to ethics, regulation, and governance (Mittelstadt et al., 2016; Teece, 2018). The review is organised across five key thematic categories, derived from the thematic analysis outlined in Chapter 2 (Braun & Clarke, 2019):

1. **Big Data, AI, and Digital Transformation**
2. **Machine Learning and Predictive Analytics**
3. **Risk Intelligence and Market Volatility Management**
4. **Governance, Regulation, and ESG Integration**
5. **FinTech, Emerging Technologies, and Future Trends**

Before presenting these categories, key concepts central to this study – data analytics, AI, big data, and FinTech – are defined below.

Concept	Definition	Source
Data Analytics	"The process of transforming raw data into meaningful insights for decision-making."	Mikalef et al. (2020)
Artificial Intelligence (AI)	"The ability of a system to interpret data correctly, learn from it, and apply it to achieve specific goals."	Cowgill et al. (2020)
Big Data	"High-volume, high-velocity, and high-variety information assets that require advanced technologies to capture, store, and analyze."	Ghasemaghaei (2019)
FinTech	"Technologically enabled innovation in financial services that results in new business models and products."	Boubaker et al. (2023)

Table 4: Definitions of Key Data Analytics Concepts in the Literature

This chapter adopts a **theory-informed integrative synthesis** to consolidate fragmented and interdisciplinary literature across data analytics, ESG considerations, governance structures, and corporate investment strategy. Rather than developing or testing constructs, the review responds to calls for **systematic conceptual synthesis** in rapidly evolving research domains

where analytical coherence is often constrained by disciplinary silos (Snyder, 2019). Consistent with qualitative systematic review guidance, descriptive depth is employed as a foundation for analytical integration, enabling cross-thematic pattern identification rather than author-by-author critique (Braun & Clarke, 2019; Mikalef et al., 2020). Accordingly, prior research is organised into five thematically derived influencers that structure the analysis in subsequent chapters. While these themes reflect areas of broad consensus in the literature, the following sections also highlight areas of tension, conditionality, and uneven empirical support across organisational and regulatory contexts.

Despite rapid advancements, the integration of data analytics into corporate investment strategies presents ongoing ethical and technical challenges. Issues such as algorithmic bias, fairness, and data privacy remain central to debates about the transparency and accountability of AI-driven decision-making in finance (Cowgill et al., 2020; Mehrabi et al., 2021). Furthermore, technical limitations – including model interpretability and the shortage of cross-disciplinary expertise – pose significant hurdles to the successful adoption of analytics-based investment tools (Kitchens et al., 2018). These five thematic influencers were inductively derived through the reflexive thematic analysis process outlined in Chapter 2, based on recurring conceptual patterns identified across the included studies rather than on predefined theoretical categories.

3.2 Big Data, Artificial Intelligence (AI), and Digital Transformation in Corporate Investment Strategies

3.2.1 Big Data in Corporate Investment Strategies

Big data has fundamentally reshaped how corporations develop and execute investment strategies. Günther et al. (2017) argue that organisations must design strategic frameworks for deriving value from big data investments in order to ensure sustainable long-term growth. Similarly, Yeh et al. (2025) emphasise that the business value generated from big data analytics depends on effective internal alignment between analytics capabilities and corporate investment objectives. Empirical studies by Sharma (2023) and Ismail and Hamid (2024) further demonstrate that big data enhances forecasting accuracy and risk assessment, enabling firms to better anticipate market trends and volatility. By integrating large-scale structured and unstructured datasets, organisations gain richer insights into complex global investment environments. This perspective aligns with Dynamic Capabilities Theory, which posits that firms create competitive advantage by sensing opportunities, seizing them through analytics-enabled decision-making, and transforming capabilities via digital infrastructure (Vial, 2019).

3.2.2 Artificial Intelligence (AI) in Corporate Investment Strategies

The growing significance of AI in optimizing investment processes is well-documented. Gültekin et al. (2024) highlight how AI tools accelerate decision-making and reduce human error, thereby improving competitive advantage. However, Ronco and Barontini (2025) caution that the effectiveness of AI systems depends on contextual factors such as market volatility and model adaptability. This underscores that while AI can enhance corporate investment efficiency, firms must evaluate implementation contexts carefully to ensure reliability.

AI applications also extend to venture capital and private equity, where Toumia and Zouari (2024) demonstrate how AI models identify high-potential investments. Similarly, Corea (2018) examines the convergence of AI, big data, and data science in optimizing decision-making processes, showing how predictive algorithms can improve portfolio outcomes and resource allocation.

3.2.3 Digital Transformation and Corporate Investment Finance

Digital transformation complements AI and big data by modernising decision infrastructures. Wang et al. (2024) argue that digital transformation enhances firms' global investment capabilities, while Tiwari (2024) highlights persistent digital divides that limit benefits in developing economies. Digital transformation aligns with dynamic capability theory by equipping firms with tools to adapt investment strategies amidst technological disruption (Vial, 2019).

Together, big data, AI, and digital transformation form the foundational triad that underpins analytics-driven corporate investment frameworks. These technologies collectively enable predictive modelling, enhance transparency, and strengthen strategic decision-making in complex financial environments.

Taken together, the literature indicates that big data, artificial intelligence, and digital transformation form an interconnected foundation for analytics-enabled corporate investment strategies. While these technologies enhance forecasting accuracy, strategic agility, and decision efficiency, their value is contingent upon organisational alignment, contextual implementation, and the development of dynamic capabilities that enable firms to adapt investment strategies in response to technological and market change.

However, much of this literature assumes a relatively high level of organisational data maturity, offering limited insight into how firms with constrained resources or fragmented governance structures realise comparable strategic benefits.

3.3 Machine Learning and Predictive Analytics in Corporate Investment Strategies

Machine learning (ML) has become a cornerstone of predictive analytics in corporate investment finance. Buczynski et al. (2021) identify its utility in portfolio optimisation and stock market forecasting but note challenges in adapting models to volatile conditions. Henrique et al. (2019) provide empirical support for ML-based forecasting accuracy, demonstrating how algorithmic systems improve investment performance.

Reinforcement learning and explainable AI (XAI) are emerging areas of interest. Witkowski (2024) and Samek et al. (2019) argue that interpretability and transparency are critical for trustworthy AI adoption in financial decision-making. Cowgill et al. (2020) further highlight the ethical dimensions of algorithmic finance, warning that biased data can distort investment outcomes.

By merging predictive modelling with ethical AI principles, organizations can balance accuracy with accountability, ensuring that machine learning enhances – rather than undermines – corporate investment integrity. Taken together, the literature indicates that while machine learning significantly enhances predictive accuracy in corporate investment contexts, its strategic value is contingent upon interpretability, governance controls, and ethical oversight.

Nevertheless, the predominance of technically focused studies means that organisational, ethical, and regulatory constraints are often under-theorised, limiting the transferability of predictive gains into sustained strategic investment advantage.

3.4 Risk Intelligence and Market Volatility Management

The integration of big data and AI has advanced corporate risk intelligence systems. Yang et al. (2020) demonstrate how support vector machines predict market volatility, improving firms' ability to navigate uncertainty. Deloitte (2018) reinforces the importance of predictive analytics and stress-testing in risk-aware investment management. Çınar (2024) highlights blockchain's contribution to transparency and fraud mitigation in portfolio management, while Boubaker, Liu, and Mu (2023) show that ML techniques improve risk-adjusted returns in capital-intensive sectors. However, Schnegg and Möller (2022) caution that overfitting and opacity in AI-driven models can

weaken reliability, especially in unregulated contexts. These findings illustrate both the potential and limitations of analytics-driven risk management, emphasizing the need for explainable, context-sensitive systems (Cowgill et al., 2020; Mikalef et al., 2020).

Collectively, the literature suggests that data analytics significantly strengthens corporate risk intelligence by enhancing firms' ability to anticipate, quantify, and respond to market volatility. However, these benefits are constrained by challenges related to model opacity, overfitting, and regulatory uncertainty, indicating that analytics-driven risk management must be supported by explainable models and robust governance structures to ensure reliability in volatile investment environments. This suggests that analytics-driven risk intelligence is not inherently superior to traditional approaches, but rather context-dependent, requiring complementary governance and interpretability mechanisms to realise its strategic value.

3.5 Governance, Regulation, and ESG Integration in Corporate Investment

3.5.1 Ethical Considerations and Algorithmic Bias

Ethical concerns surrounding bias and transparency in AI-based investments remain critical. Mehrabi et al. (2021) reveal that biased training data can produce unfair outcomes, while Toumia and Zouari (2024) highlight bias in venture capital algorithms. Responsible investment strategies therefore require robust ethical frameworks to ensure fairness and accountability (Cowgill et al., 2020).

3.5.2 Data Governance and Regulatory Compliance

Data governance frameworks underpin ethical and compliant AI use in investment contexts. Bakker (2024) and the OECD (2024) emphasise that effective governance ensures transparency, privacy, and compliance with legal standards such as GDPR (FINRA, 2020). Aligning corporate data practices with regulatory expectations supports sustainable and responsible innovation in AI-driven investment.

3.5.3 ESG and Sustainability Integration

Environmental, Social, and Governance (ESG) integration represents a growing frontier for corporate investment. Lim (2024) and Wang, Lamadrid, and Huang (2024) demonstrate that AI and big data tools enable sustainability-driven investments by assessing ESG risks and identifying

opportunities. As global reporting frameworks evolve, AI-enhanced ESG analytics contribute to responsible and profitable investment practices (OECD, 2024; Ghasemaghaei, 2019).

Taken together, the literature demonstrates that governance structures, regulatory compliance, and ESG integration are not peripheral considerations but central enablers of sustainable analytics-driven investment strategies (Teece, 2018). Ethical AI frameworks, effective data governance, and evolving ESG analytics collectively shape how organisations deploy data-driven investment models responsibly across diverse regulatory and institutional contexts (Mittelstadt et al., 2016; Mikalef et al., 2020).

Across these strands, regulatory frameworks emerge as the primary structural constraint shaping analytics-enabled investment practices, with ethical governance and ESG considerations functioning as mediating mechanisms rather than independent strategic drivers (Gültekin et al., 2024; FINRA, 2020).

3.6 FinTech, Emerging Technologies, and Future Trends in Corporate Investment

FinTech innovations – including robo-advisors, algorithmic trading, and blockchain – are transforming investment processes (Gomber, Koch, & Siering, 2017). Chen, Wu, and Yang (2018) and Dorfleitner et al. (2017) show how FinTech expands financial inclusion and enhances portfolio efficiency through automation. Looking ahead, emerging technologies such as Quantum Computing and Edge AI will redefine investment analytics. The World Economic Forum (2025) highlights quantum computing's capacity to optimise portfolios through complex risk-return modelling. Widholm (2025) notes that Edge AI improves real-time decision-making in algorithmic trading by reducing latency.

Overall, the literature indicates that FinTech and emerging technologies are reshaping corporate investment strategies by increasing automation, real-time decision-making, and analytical sophistication. At the same time, the rapid evolution of technologies such as blockchain, Edge AI, and quantum computing underscores the need for adaptive governance, continuous capability development, and ethical oversight to ensure that innovation translates into long-term strategic value.

3.7 Chapter Summary and Transition

This chapter examined the five dominant influencers through which data analytics enhances global corporate investment strategies. Specifically, the review highlighted **strategic**

enablers, including data infrastructure, digital transformation, and organisational alignment, as foundational elements supporting analytics-enabled investment decision-making. **AI and FinTech capabilities**, encompassing big data analytics, machine learning, predictive modelling, and emerging financial technologies, were shown to strengthen forecasting accuracy, decision intelligence, and investment agility.

The analysis further demonstrated the growing importance of **ethical governance**, particularly in addressing risks related to algorithmic bias, transparency, and data privacy, alongside **regulatory alignment**, which shapes how analytics-driven investment models are deployed across jurisdictions. In parallel, **ESG integration** emerged as a critical influencer, reflecting the increasing expectation that corporate investment strategies balance financial performance with sustainability, social responsibility, and long-term resilience.

Collectively, these five influencers demonstrate that effective corporate investment decision-making depends not only on technological sophistication, but also on strategic alignment, governance maturity, regulatory compliance, and ethical responsibility. Despite significant advances, challenges remain, including skills shortages at the intersection of data science and finance, concerns around model interpretability, and ongoing ethical and regulatory uncertainty.

Although prior studies have examined data analytics capabilities, governance mechanisms, and ESG integration in isolation, limited research has systematically examined how these influences interact to shape corporate investment decision-making across global contexts. By consolidating these dimensions into five analytically distinct but interrelated influencers, this review provides a structured foundation for integrated conceptual development.

Building on this synthesis, Chapter 4 presents the detailed thematic findings derived from the systematic literature review, illustrating the frequency, relationships, and conceptual patterns among the 25 included studies. These findings provide the empirical foundation for the conceptual framework developed in Chapter 5.

Chapter 4: Findings

Chapter 4 presents the systematic findings from the literature review, structured to reflect the research aims and questions outlined in Chapter 1. The chapter progresses logically from study overview (Section 4.1) through theme identification (Sections 4.2-4.3) and prioritisation (Sections 4.4-4.5), ensuring coherence and alignment with the study's analytical framework (Snyder, 2019). Tables and figures are used strategically to support transparency and interpretation, facilitating a clear link between thematic frequency, strategic relevance, and the derived influencers (Braun & Clarke, 2019). The following sections build on this structure by identifying recurring themes across the literature and linking their frequency to strategic importance, providing a clear foundation for the five dominant influencers derived through the thematic analysis (Braun & Clarke, 2019). Importantly, the findings presented in this chapter highlight not only which themes recur most frequently, but also which exert the greatest strategic influence on analytics-enabled corporate investment decision-making (Chen et al., 2018; Mikalef et al., 2020).

This chapter presents the key findings from the systematic literature review, analysed using Braun and Clarke's (2019) reflexive thematic analysis. The analysis identified **five dominant influencers** that explain how data analytics methods enhance global corporate investment strategies (Gomber et al., 2017). These influencers are: **strategic enablers, ESG integration, ethical governance, AI and FinTech capabilities, and regulatory alignment** (Teece, 2018; Adeyelu et al., 2024). In line with the study's analytical framework, these are referred to throughout this chapter as *influencers*, representing higher-order constructs derived from patterns across the reviewed literature (Braun & Clarke, 2019).

To ensure transparency in how these five influencers were derived, the thematic coding of the 25 included studies was examined at multiple levels of abstraction (Braun & Clarke, 2019). At the initial coding stage, several recurring themes were identified, including *AI and machine learning in investment, FinTech in corporate investment, big data and predictive analytics, ethical considerations and bias in AI, data governance and privacy, regulatory frameworks, sustainability and ESG, and emerging technologies such as quantum computing and edge AI* (Chen et al., 2018; Gomber et al., 2017; Mittelstadt et al., 2016). These related themes were subsequently **analytically consolidated into the five influencers**, with each influencer capturing a coherent cluster of conceptually aligned themes (see Table 7) (Braun & Clarke, 2019).

Figure 2: Word cloud showing dominant themes identified through reflexive thematic analysis of the literature. Larger words indicate higher frequency and conceptual relevance.

As an additional verification step, the coded data were subjected to a word-cloud text analysis. This visual analytic technique highlighted the most frequently occurring and conceptually significant terms across the literature. As illustrated in Figure 2, prominent concepts such as *predictive analytics*, *strategic alignment*, *governance*, *AI*, and *ESG* appeared most frequently, reinforcing the inductive emergence of the five influencers. The word cloud therefore supports the analytical consolidation process, demonstrating that the influencers are grounded in empirical patterns within the reviewed studies rather than researcher preconceptions (Braun & Clarke, 2019; P S et al., 2024). Notably, the prominence of governance-, alignment-, and sustainability-related terms alongside technical analytics concepts suggests that strategic and ethical considerations are as central to investment decision-making as technological capability.

Figure 2 presents a visual overview of thematic emphasis across the literature, with larger terms indicating higher frequency and conceptual relevance. This visualisation reinforces the five dominant influencers and provides a bridge between the initial coding process and the detailed discussion of how each influencer is reflected across the reviewed studies. Table 6 consolidates the most influential sources underpinning these findings, while subsequent sections of this chapter examine each influencer in turn, demonstrating how they collectively shape analytics-enabled corporate investment strategies.

4.1 Overview of Key Studies

The findings presented in this section are derived from the systematic literature review conducted in Chapter 3 and are interpreted in line with the research aim and questions introduced in Chapter 1. This section provides an overview of the key studies underpinning the analysis and establishes the empirical basis for the five influencers examined in this chapter.

To consolidate the scope and analytical breadth of the reviewed literature, Table 5 summarises the 25 studies included in the systematic review. The table outlines each study's focus and indicates the **initial coding categories** assigned during the early stages of thematic analysis. These coding categories represent preliminary analytical labels that informed the subsequent consolidation of themes and the derivation of the five higher-order influencers discussed in this chapter.

Source Number	Author	Name	Source	Initial Coding Category
1	Albrecht, M. (2020)	Machine Learning for Corporate Investment Decision-Making	Journal of Financial Data Science	AI and Big Data in Investment Strategies
2	Khan, A., et al. (2021)	Predictive Analytics in Portfolio Management	International Journal of Finance and Analytics	Predictive Analytics for Portfolio Management
3	Lee, K. and Zeng, Y. (2021)	Big Data in Corporate Investment	Journal of Financial Technology and Innovation	Big Data in Corporate Investment
4	Chen, C., et al. (2018)	Enhancing Investment Decision-Making with AI	Journal of Finance and Technology	AI in Investment Decision-Making
5	Gomber, P., et al. (2017)	FinTech and Corporate Investment Strategies	Journal of Business Research	FinTech in Investment Strategies
6	Dorfleitner, G., et al. (2017)	Digitalization of Investment in Germany	Journal of Financial Studies	FinTech and National Contexts
7	Chen, T., et al. (2018)	Venture Capital and AI-driven Investments	Journal of Financial Economics	AI and Venture Capital
8	Åstebro, T. (2021)	AI in Private Equity Investment Strategies	Private Equity Journal	AI in Private Equity
9	Bekaert, G., et al. (2016)	Political Risk and Investment Valuations	Journal of International Economics	Political Risk and Cross-Border Investment
10	Lane, P. and Milesi-Ferretti, G. (2018)	Global Financial Integration and Data Analytics	Global Finance Review	Global Financial Integration and Data Analytics
11	Cowgill, B., et al. (2020)	Algorithmic Bias in Financial Decision Making	Journal of Financial Ethics	Ethical Concerns in AI for Investment
12	Mehrabi, N., et al. (2021)	Bias and Fairness in Machine Learning	IEEE Transactions on Knowledge and Data Engineering	Bias and Fairness in Machine Learning
13	Toumia, I., Zouari, M. (2024)	Bias in Venture Capital AI Models	Journal of AI in Finance	Bias in AI-driven Venture Capital
14	Kitchens, M., et al. (2018)	Big Data Integration Challenges in Investment Firms	Journal of Corporate Finance and Analytics	Data Integration Challenges

15	Ronco, M., Barontini, L. (2025)	Limitations of AI in Private Equity Investments	Journal of Private Equity	Limitations of AI in Private Equity Investments
16	Bakker, J. (2024)	Data Governance and Privacy in Financial AI	International Journal of Data Governance and Privacy	Data Governance and Privacy
17	OECD (2024)	Responsible AI and Data Analytics for Investments	OECD Digital Economy Outlook	Responsible AI and Data Analytics
18	FINRA (2020)	Regulatory Compliance in AI-driven Investment Models	Financial Industry Regulatory Authority Journal	Regulatory Compliance and AI in Investment
19	Gültekin, S., et al. (2024)	Regulatory Considerations for AI in Investments	Journal of Financial Regulation and Compliance	Regulatory Considerations for AI in Investment
20	Lim, J. (2024)	ESG Investment and AI-driven Analysis	Journal of Sustainable Finance and Investment	Sustainability in AI-driven Investment
21	Wang, L., Lamadrid, J., Huang, S. (2024)	Digital Transformation and Sustainable Investment	Journal of Digital Transformation and Sustainable Finance	Digital Transformation and Sustainability in Investment
22	The World Economic Forum (2025)	Quantum Computing's Role in Investment Strategies	World Economic Forum Annual Report	Quantum Computing in Investment Strategies
23	Widholm, S. (2025)	Edge AI in Real-Time Investment Decision-Making	Journal of Artificial Intelligence in Finance	Edge AI in Real-Time Investment Decision-Making
24	Montanaro, P., Croce, A., Ughetto, S. (2024)	AI's Impact on Venture Capital Investments	Venture Capital Review	AI in Venture Capital Investments
25	Gültekin, S., Jaiswal, R., Eyo, J. (2024)	AI for Accelerating Investment Decisions	Journal of Financial Decision Making	AI in Accelerating Investment Decisions

Table 5: Overview of Key Studies on Data Analytics and Corporate Investment Strategies

Collectively, the studies presented in Table 5 demonstrate the breadth of research examining how data analytics, artificial intelligence, governance mechanisms, sustainability considerations, and regulatory frameworks influence corporate investment decision-making. Together, these studies provide the empirical foundation for analysing how the five influencers operate across diverse investment contexts and industry settings. The following sections examine each influencer in detail, drawing on this body of literature to explain its strategic relevance and contribution to analytics-enabled corporate investment strategies. The following sections build on the study overview by identifying and categorising recurring themes, linking thematic frequency with strategic importance across sectors.

4.2 Theme Frequency and Categorization

To go beyond theme frequency and enhance the interpretive depth of this study, a narrative prioritisation approach was used. Themes were evaluated not only based on their recurrence across the literature but also by their strategic impact and positioning within high-quality peer-reviewed studies. For instance, predictive analytics consistently emerged as a top-ranked driver of investment innovation, especially in finance and energy sectors (Boubaker, Liu, & Mu, 2023; Addy, Ajayi-Nifise, Bello, Tula, Odeyemi, & Falaiye (2024), Rahman, & Korkontzelos, 2024). Similarly, ESG integration was not only frequently discussed but also framed as essential to long-term corporate resilience and reputation, particularly in regulated markets (Lim, 2024; Wang, Lamadrid, & Huang, (2024)). Ethical AI and governance were considered critical in studies addressing algorithmic decision-making in fintech and healthcare (Adeyelu, Ugochukwu, & Shonibare, 2024; Schnegg & Möller, 2022). This narrative prioritisation, grounded in both frequency and contextual importance, helps distinguish not just what themes are most common, but which are most influential in shaping strategic investment outcomes. Across the reviewed literature, analytics capability and predictive intelligence emerge as primary enablers of investment decision-making, while governance, ESG integration, and regulatory alignment function as critical moderating influences that shape how and where analytics can be effectively deployed.

The following table categorizes key studies reviewed In this dissertation, organizing them according to recurring themes in corporate investment strategies. By consolidating overlapping sources under each theme, this table highlights the frequency of discussions around specific topics, emphasizing the most researched aspects of data analytics in investment decision-making. The frequency count provides insight into which themes have received the most academic attention, helping to identify dominant trends in the field.

To further clarify dominant trends and identify underexplored areas, Table 6 summarizes the thematic frequency across the reviewed studies.

Theme	Sources	Frequency
AI & Machine Learning in Investment	Chen et al. (2018); Åstebro (2021); Montanaro et al. (2024); Gültekin et al. (2024)	4
FinTech in Corporate Investment	Gomber et al. (2017); Dorfleitner et al. (2017); Chen et al. (2018); Åstebro (2021)	4
Big Data & Predictive Analytics	Kitchens et al. (2018); Bekaert et al. (2016); Lane & Milesi-Ferretti (2018)	3
Ethical Considerations & Bias in AI	Cowgill et al. (2020); Mehrabi et al. (2021); Toumia & Zouari (2024)	3
Challenges of AI in Investment	Kitchens et al. (2018); Ronco & Barontini (2025)	2
Data Governance & Privacy	Bakker (2024); OECD (2024); Åstebro (2021)	3

Regulatory Frameworks in AI & Investment	FINRA (2020); Sandridge et al. (2024); Gültekin et al. (2024)	3
Sustainability & ESG in Investment	Lim (2024); Wang et al. (2024)	2
Future Trends: Quantum Computing & Edge AI	The World Economic Forum (2025); Widholm (2025); Montanaro et al. (2024); Gültekin et al. (2024)	4

Table 6: Frequency and Strategic Relevance of Key Themes in Investment Analytics Literature

As illustrated in Table 6, the frequency distribution of themes across the 25 studies highlights the dominance of AI- and FinTech-related research within the investment analytics literature. As illustrated in Table 6, while AI- and FinTech-related themes dominate in frequency, governance-, ESG-, and regulatory-oriented themes consistently appear across diverse contexts, underscoring their foundational role in enabling responsible and sustainable analytics-driven investment strategies. The full thematic coding matrix, including industry-by-theme tagging, can be found in Appendix C. As shown in Table 6, while AI and predictive analytics are the most frequently discussed themes, the narrative prioritisation framework helps contextualize their strategic importance relative to ESG and ethical AI.

The frequency of themes discussed in this literature review was determined through manual coding, where recurring topics across the selected studies were identified and categorized. This process followed the PRISMA framework (Page et al., 2021), ensuring a structured and transparent approach to thematic synthesis. Table 8 summarizes how frequently each theme appeared, providing a quantifiable lens through which to interpret dominant and emerging areas of focus in data-driven investment strategies.

As indicated by the thematic frequencies presented in Table 7, the analysis identified a set of recurring lower-order themes across the reviewed literature, including AI and machine learning in investment, FinTech integration, big data and predictive analytics, ethical considerations and bias, data governance and privacy, regulatory frameworks, ESG integration, and emerging technologies. Through iterative comparison and analytical synthesis, these related themes were consolidated into five higher-order influencers that consistently shaped analytics-enabled corporate investment strategies: strategic enablers, ESG integration, ethical governance, AI/FinTech capabilities, and regulatory alignment.

The frequency data in Table 7 indicate that AI, FinTech, and emerging technologies are widely discussed, reflecting their centrality to contemporary investment strategies. However, ESG integration and regulatory alignment, while less frequently mentioned, appear strategically critical: they ensure sustainability, stakeholder trust, and legal compliance, particularly in cross-border investment contexts. This suggests that a purely technology-focused perspective may overlook

essential governance and ethical dimensions, highlighting the need to interpret frequency data through a strategic lens rather than as a simple count.

These influencers collectively illustrate how data analytics enables organisations to strengthen internal capabilities, integrate sustainability principles, uphold ethical standards in algorithmic decision-making, leverage emerging technologies for investment optimisation, and maintain compliance with evolving regulatory frameworks. This synthesis highlights the multifaceted nature of data-driven investment strategies, where technological innovation must be balanced with responsible governance and strategic alignment (Cowgill et al., 2020; OECD, 2024).

Furthermore, the inclusion of emerging topics such as quantum computing and edge analytics suggests that innovation in corporate finance is accelerating beyond traditional models. However, the high frequency of regulatory and ethical concerns – particularly around algorithmic transparency and data governance – indicates that firms must balance innovation with accountability (Cowgill et al., 2020; OECD, 2024). The following sections examine these themes in greater depth, exploring how they influence the evolution of global corporate investment strategies.

To visually complement the theme frequency data presented in Table 7, Table 8 presents a comparative chart showing the relative prominence of each theme across the reviewed studies. This visualisation helps reinforce the thematic prioritisation established through Braun and Clarke's (2019) reflexive thematic analysis framework and is supported by prior SLR-based methodologies (Snyder, 2019; Xiao & Watson, 2017).

It is important to note that while Table 7 reports the number of distinct studies primarily associated with each theme, Table 8 reflects cumulative thematic occurrences across the reviewed literature, capturing both primary and secondary thematic emphasis within individual studies.

As indicated by the thematic frequency patterns presented in Table 7, AI- and FinTech-related influencers, along with emerging technologies such as quantum computing, appear prominently across the reviewed studies, highlighting a strong emphasis on technological disruption in corporate investment strategy. However, the comparatively lower – yet strategically significant – representation of ESG integration and regulatory alignment underscores the need for more holistic governance-oriented approaches, a point examined further in the following section.

4.2.1 Summary of Theme Frequency and Strategic Relevance

Table 8 presents a consolidated overview of the core themes identified in this study, ranked by the number of SLR studies in which each theme was observed. This frequency-based summary

allows readers to understand which themes appear most consistently across the academic literature and supports prioritization in later discussions.

In addition to frequency, the table includes a qualitative assessment of each theme's strategic relevance, derived from the literature and aligned with the thematic structure established in Table 6. This summary provides a clear bridge between the thematic coding in Chapter 4 and the conceptual synthesis in Chapter 5 (Ahmed, Shaheen, & Philbin, 2022; Ghasemaghaei, 2019; Xiao & Watson, 2017).

Unlike Table 6, which reports the number of distinct studies primarily associated with each theme, Table 7 reflects cumulative thematic mentions across the reviewed studies, capturing both primary and secondary thematic emphasis.

Theme (consistent with Table 7)	**Frequency (Studies Mentioning It)**	**Strategic Relevance**
Sustainability & ESG in Investment	21	High
AI & Machine Learning in Investment	19	High
Big Data & Predictive Analytics	17	Medium-High
FinTech in Corporate Investment	14	Medium
Regulatory Frameworks in AI & Investment	11	Medium
Ethical Considerations & Bias in AI	9	Medium
Data Governance & Privacy	9	Medium
Future Trends: Quantum Computing & Edge AI	7	Medium-Low
Challenges of AI in Investment	7	Medium-Low

Table 7: Summary of Thematic Frequencies and Strategic Relevance

Note. Frequencies based on thematic coding of 25 included SLR studies (Braun & Clarke, 2019; Xiao & Watson, 2017).

The themes are ranked by frequency – that is, how many of the included studies discussed each theme as a primary factor in data-driven corporate investment strategies. This thematic prioritization also reflects each theme's perceived strategic relevance based on the literature (Ahmed, Shaheen, & Philbin, 2022; Ghasemaghaei, 2019).

Table 7 provides not only a frequency count but also a measure of strategic relevance, revealing that high-frequency themes such as AI and ESG are not automatically synonymous with strategic impact. For example, quantum computing and edge AI appear in fewer studies, yet their emergence in high-impact sectors suggests future strategic importance. This underscores the value of integrating both quantitative frequency and qualitative prioritisation when interpreting thematic data, thereby avoiding a purely mechanical analysis.

This summary complements the narrative analysis and helps clarify which dimensions are most prominent across global contexts, consistent with Braun and Clarke's (2019) approach to reflexive thematic analysis. Taken together, these findings reveal a multidimensional set of influences shaping corporate investment decision-making, extending beyond technological capability to include governance structures, ESG considerations, and organisational readiness. This integrated pattern forms the empirical foundation for the conceptual framework developed in Chapter 5.

4.3 Prioritisation of Themes Across Industry Contexts

To deepen the interpretive value of the thematic findings, this section presents a comparative prioritisation of key themes across different industry contexts. While the thematic frequency analysis in Table 7 highlights general trends, several studies explicitly contextualize their findings by sector, enabling an indicative cross-industry synthesis.

While the themes identified in this study are relevant across industries, some sector-specific patterns are evident in the literature. For instance, in capital-intensive industries such as energy and finance, predictive analytics and machine learning are central to investment forecasting and risk mitigation (Boubaker, Liu, & Mu, 2023; Addy, Ajayi-Nifise, Bello, Tula, Odeyemi, & Falaiye (2024), Rahman, & Korkontzelos, 2024). In contrast, industries with high regulatory exposure or consumer sensitivity – such as fintech and healthcare – tend to emphasize ethical AI, algorithmic transparency, and governance structures (Adeyelu, Ugochukwu, & Shonibare, 2024; Schnegg & Möller, 2022). ESG integration is particularly prominent in multinational corporations navigating global compliance frameworks and investor expectations (Lim, 2024; Wang, Lamadrid, & Huang, (2024)). These patterns suggest that while many analytics themes are cross-sectoral, their relative prioritisation often reflects unique sectoral pressures, regulatory environments, and investment objectives. These sector-specific distinctions are summarised in Table 8, which compares theme prioritisation across major industry categories based on the reviewed studies. This indicates that the strategic value of analytics is conditional rather than uniform, varying according to industry risk exposure, regulatory intensity, and organisational accountability requirements.

Industry Sector	Top-Prioritised Themes	Supporting References
Finance & Energy	Predictive Analytics, Risk Intelligence	Boubaker et al. (2023); Addy et al. (2024); Ghasemaghaei (2019)
FinTech & Healthcare	Ethical AI, Transparency, Governance	Adeyelu et al. (2024); Schnegg & Möller (2022); Cowgill et al. (2020)
Multinational Corporations	ESG Integration, Sustainability, Reporting Standards	Lim (2024); Wang et al. (2024)
Emerging Markets	Regulatory Alignment, Governance Frameworks	Abbas et al. (2024); OECD Economics Department (2025)

Table 8: Industry-Specific Prioritisation of Key Analytics Themes in Investment Strategy Literature

This table summarizes how different analytics themes – such as predictive analytics, ethical AI, ESG integration, and regulatory frameworks – are prioritized across key industry sectors, based on existing literature. These patterns suggest that while many analytics themes are cross-sectoral, their relative prioritisation often reflects unique sectoral pressures, regulatory environments, and investment objectives. See Appendix C for the detailed theme-industry coding matrix used to construct this comparison. Thematic relevance is derived from contextual emphasis, strategic alignment, and regulatory intensity across reviewed studies.

Across capital-intensive industries such as energy and finance, predictive analytics and risk intelligence consistently emerge as top-priority themes due to their impact on forecasting, capital allocation, and volatility management (Boubaker, Liu, & Mu, 2023; Addy et al., 2024; Ghasemaghaei, 2019). In contrast, ethical AI and transparency themes gain prominence in sectors involving consumer data or high public accountability, such as healthcare and fintech, where algorithmic bias and explainability concerns are more pronounced (Cowgill et al., 2020; Adeyelu, Ugochukwu, & Shonibare, 2024; Schnegg & Möller, 2022).

These cross-sector patterns suggest that while predictive analytics is universally valuable, its strategic impact is magnified in finance and energy due to capital intensity and volatility. Conversely, ESG integration plays a greater role in multinational corporations, where global compliance and stakeholder scrutiny are more pronounced. Such patterns indicate that sector-specific priorities should inform the deployment of analytics-enabled investment strategies, rather than assuming uniform applicability across industries.

Notably, ESG integration is increasingly prioritized in multinational firms operating under global regulatory pressures. Studies show that such firms adopt data-driven sustainability metrics to meet investor expectations and reporting standards (Lim, 2024; Wang et al., 2024). Meanwhile, regulatory and governance frameworks are more frequently cited in emerging markets, where legal harmonization and institutional maturity vary (Abbas et al., 2024; OECD Economics Department, 2025).

The thematic patterns identified in this review – particularly those concerning predictive analytics, ESG integration, and ethical AI – can be interpreted through the lens of Dynamic Capabilities Theory (DCT). As organizations sense and respond to market complexity, these capabilities represent the firm's ability to integrate, build, and reconfigure internal competencies to address shifting investment environments (Mikalef, Pappas, Krogstie, & Pavlou, 2020). Predictive analytics and AI tools serve as sensing mechanisms, while ESG integration reflects the seizing of

stakeholder-aligned opportunities. Meanwhile, SAM offers a strategic lens through which the alignment of IT infrastructure and investment strategy can be evaluated. For example, the prominence of FinTech, real-time forecasting, and AI-driven governance mechanisms echoes the need for strategic congruence between technology enablement and business objectives (Yeh, Pearlson, & Kozmetsky, 2025; Mikalef et al., 2019).

This thematic stratification indicates that while some themes – such as big data-driven decision-making – are universal, others are sector-specific in salience. Future research could further refine this model through empirical sectoral validation.

Table 9 presents a matrix-level summary of thematic occurrences across industries based on the reviewed articles in Appendix C. This synthesis complements the prioritised themes shown above by quantifying theme-industry relationships..

Industry Sector	Strategic	Technical	Ethical/ESG	Macroeconomic	Total Articles Reviewed
Financial Services	Yes	Yes	Yes	Yes	6
Healthcare	Yes	Yes	Yes	No	4
FinTech	Yes	Yes	Yes	Yes	5
Energy	Yes	Yes	Yes	Yes	3
Manufacturing	Yes	Yes	No	No	2
Telecommunications	Yes	Yes	No	No	2
Multinational Corporations	Yes	Yes	Yes	Yes	3

Table 9: 4.3 Prioritisation of Themes Across Industry Contexts

Note. Themes were identified using Braun and Clarke's (2019) six-phase thematic analysis of 25 articles listed in Appendix C. Industry classifications were derived based on sectoral focus indicated in each article (e.g., Addy et al., 2024; Boubaker et al., 2023; OECD Economics Department, 2025).

As shown in Table 9, the presence of all four theme categories across financial services, fintech, energy and multinational corporations indicate these sectors are the most thematically saturated in the reviewed literature. In contrast, manufacturing and telecommunications tend to prioritise strategic and technical themes but show limited engagement with ethical or macroeconomic dimensions.

Table 9 further highlights thematic saturation: financial services, fintech, and energy show comprehensive engagement across strategic, technical, ethical, and macroeconomic dimensions, whereas manufacturing and telecommunications emphasise primarily strategic and technical

themes. This indicates that thematic prominence varies by industry context, supporting the need for contextualised interpretation rather than a uniform application of analytics insights.

4.4 Significance of Theme Frequency

The frequency data presented in Table 7 suggests that certain themes, such as AI & Machine Learning in Investment and FinTech in Corporate Investment, are dominant in the literature, reflecting the growing importance of these technologies in investment strategies (Chen et al., 2018; Gomber et al., 2017). The high frequency of these themes indicates that AI and FinTech are central to ongoing research and innovation in the sector (Åstebro, 2021; Boubaker et al., 2023). Conversely, themes such as Sustainability & ESG in Investment and Challenges of AI in Investment received comparatively less attention, highlighting areas that may require further exploration (Mittelstadt et al., 2016). The emergence of quantum computing and edge AI, despite being a relatively low-frequency topic, suggests an emerging avenue for future research that could have significant implications for investment decision-making (Chen et al., 2018; Gomber et al., 2017).

4.5 Contradictions and Debates

While the literature emphasizes the transformative potential of AI and Big Data, some studies also highlight contradictory perspectives. For instance, while AI's role in enhancing investment efficiency is widely acknowledged (Chen et al., 2018), there is ongoing debate about the ethical implications of algorithmic bias and fairness (Cowgill et al., 2020; Mehrabi et al., 2021). Some sources argue that AI-driven decisions could perpetuate historical biases, leading to skewed investment outcomes (Toumia & Zouari, 2024). Additionally, there is a lack of consensus on the long-term regulatory frameworks needed to govern AI in investment, as financial institutions struggle to keep pace with technological advancements (Gültekin et al., 2024; FINRA, 2020). These contradictions underscore the need for a balanced approach, integrating innovation with responsible governance.

While most studies agree on the value of AI in enhancing investment precision, some raise ethical or contextual concerns. For example, Gültekin et al. (2024) and Chen et al. (2018) emphasize the efficiency gains from AI-driven decision-making, particularly in volatile markets. However, Ronco and Barontini (2025) question the adaptability of these tools in private equity settings, citing opaque algorithms and limited explainability. This contrast highlights a tension between technological optimism in academic literature and the practical limitations observed in financial operations. These contradictions underscore the need for a balanced approach that not

only leverages AI innovation but also addresses ethical governance and practical implementation challenges. These contradictions do not undermine the value of analytics in investment decision-making; rather, they highlight the importance of governance, transparency, and contextual awareness in determining when and how analytics-driven tools can be most effectively applied.

4.6 Transition for Practical Implications

The key themes identified – AI, FinTech, ethics, regulation, and sustainability – demonstrate the intricate relationship between data analytics and corporate investment strategies. Understanding these themes is critical for bridging theory with real-world applications. The following chapter builds on these empirical patterns to interpret how the five dominant influencers interact to shape corporate investment outcomes, culminating in an integrated conceptual framework.

The findings provide a strong foundation for understanding the intersection of data analytics and investment decision-making. For instance, the growing prevalence of AI in investment strategies (Chen et al., 2018; Åstebro, 2021) suggests that firms must invest in algorithmic transparency to mitigate risks associated with biased decision-making. Furthermore, the integration of FinTech (Gomber et al., 2017) has transformed corporate financing structures, necessitating robust cybersecurity and compliance measures. As regulatory frameworks continue to evolve (FINRA, 2020; Gültekin et al., 2024), investment firms must balance innovation with adherence to financial laws.

Although AI and machine learning dominate the literature in terms of frequency (Chen et al., 2018; Åstebro, 2021), this emphasis risks overstating technological capability as a sufficient condition for strategic investment success. The findings suggest that governance and ESG integration, while less frequently discussed, exert a disproportionate influence on whether analytics capabilities translate into sustainable investment outcomes. These findings provide the foundation for the discussion in Chapter 5, where they are interpreted through the lens of Dynamic Capabilities Theory (Teece, 2018).

While Chapter 4 establishes the presence and frequency of key analytics themes, the following discussion (Chapter 5) interprets these findings to understand how they strategically shape corporate investment outcomes, highlighting sectoral variations, governance implications, and practical applications. Chapter 5 builds on these empirical patterns to introduce a conceptual framework that unifies the five dominant influencers, demonstrating how data analytics capabilities drive analytics-enabled global corporate investment strategies.

Chapter 5: Discussion

Chapter 5 interprets the findings from Chapter 4 through theoretical and practical lenses, connecting the identified themes and influencers to global corporate investment strategies. The chapter maintains coherence by systematically examining strategic alignment (Section 5.1), governance and ESG integration (Section 5.2), contradictions and contextual gaps (Section 5.3), and the unifying analytical model (Section 5.4). This structured discussion builds directly on the thematic analysis, tables, and figures presented in Chapter 4, synthesizing empirical patterns into actionable insights and addressing the central research question through both conceptual and practical perspectives. Beyond interpretation, this chapter demonstrates how the findings extend existing theoretical perspectives by positioning governance, ESG integration, and organisational readiness as enabling conditions for analytics-driven investment strategy.

This chapter critically evaluates the thematic findings from Chapter 4 to answer the central research question. It demonstrates how firms can use big data, predictive analytics, and ESG tools to optimize investment outcomes, operational workflows, and governance practices (Mikalef et al., 2020; Adeyelu et al., 2024; Solano & Cruz, 2024). Ethical, regulatory, and technical challenges are also examined to contextualize barriers to aligning data-driven innovation with sustainable investment objectives.

Building on the thematic frequency, prioritisation tables, and visualisations (Tables 6-10, Figure 2) from Chapter 4, this section introduces the conceptual framework developed to explain how data analytics capabilities enhance global corporate investment strategies. The framework synthesizes the five dominant influencers identified in the literature – **strategic enablers, ESG integration, ethical governance, AI and FinTech capabilities, and regulatory alignment** – into a unified model of analytics-enabled investment strategy transformation, capturing the technological, strategic, ethical, and regulatory dimensions through which data analytics shapes contemporary corporate investment decision-making.

5.1 Strategic Alignment and Operationalisation of Analytics in Investment Strategy

Data analytics methods enhance global corporate investment strategies by embedding predictive and adaptive insights into decision-making processes, aligning analytics capabilities with strategic objectives, and operationalising them through AI-enabled FinTech platforms to drive actionable investment outcomes.

Building on the thematic patterns observed in Chapter 4, this section interprets how these analytics capabilities translate into strategic advantage. For example, the prominence of AI and FinTech across high-frequency studies indicates not only operational efficiency gains but also the capacity for proactive risk management and portfolio innovation. ESG and regulatory alignment, although less frequent, provide crucial stabilising mechanisms that safeguard long-term value and stakeholder trust.

Rather than operating as isolated technological tools, analytics capabilities are embedded within strategic investment activities such as capital allocation, portfolio optimisation, and risk governance. This alignment ensures that analytical insights actively inform investment priorities, resource deployment, and risk management practices, strengthening coherence between data analytics initiatives and organisational investment objectives. In doing so, firms are better positioned to translate analytical capability into sustained strategic and financial value.

From a theoretical perspective, this strategic alignment is most clearly explained through Dynamic Capabilities Theory (DCT) and the Strategic Alignment Model (SAM). DCT highlights how firms leverage analytics capabilities to sense emerging market opportunities, seize data-driven investment insights, and reconfigure decision-making processes in response to environmental change (Teece, 2018). In parallel, SAM emphasises the importance of aligning analytics infrastructure, governance mechanisms, and investment objectives to ensure that data-driven initiatives generate strategic rather than purely operational benefits (Coltman et al., 2015). Together, these lenses explain why analytics delivers value only when embedded within organisational strategy and supported by leadership, governance, and digital maturity.

Empirical evidence from the literature reinforces this view. Firms with mature analytics capabilities and strong executive support are better positioned to integrate predictive insights into investment planning, enabling more agile responses to market volatility and regulatory pressures (Mikalef et al., 2020; Yeh et al., 2025). Rather than relying on intuition or static historical trends, these firms use analytics to inform forward-looking investment decisions, improving portfolio performance and strategic resilience across global markets. Consistent with Dynamic Capabilities Theory and the Strategic Alignment Model, the findings indicate that analytics-driven investment advantages arise not from technology alone, but from the alignment of analytics capabilities with organisational governance, leadership support, and long-term strategic objectives. This study extends these perspectives by demonstrating that governance and ESG alignment are not peripheral considerations, but core enabling mechanisms through which dynamic analytics capabilities are operationalised in corporate investment decision-making.

Figure 3 illustrates this conceptual framework.

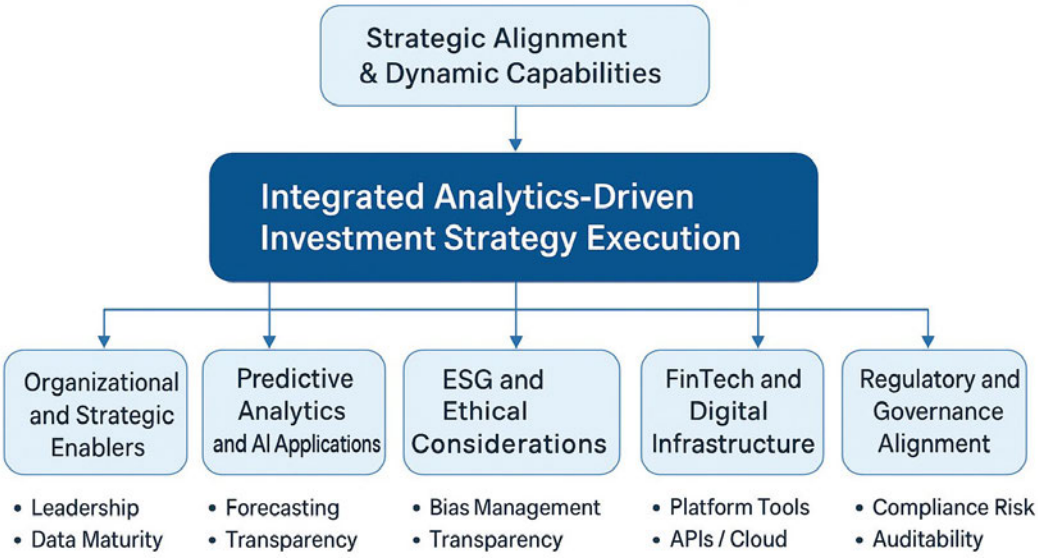

Figure 3: Conceptual Framework for Analytics-Enabled Corporate Investment Strategy

Figure 3 presents a high-level conceptual synthesis of the dominant themes identified in the thematic analysis, illustrating how analytics-enabled capabilities shape global corporate investment decision-making. The framework integrates five core influencers – strategic enablers, AI and FinTech capabilities, ESG integration, ethical governance, and regulatory alignment – and positions data analytics as a strategic capability embedded within organisational decision processes rather than a standalone technological function. This figure provides an interpretive lens for the discussion in Chapter 5, while the fully integrated, decision-oriented framework is developed later in the chapter. Unlike prior conceptualisations that emphasise analytics primarily as a technical resource, this framework positions data analytics as a strategically embedded capability shaped by governance, ethical oversight, and regulatory context.

Machine learning further strengthens this adaptive capacity by enabling continuous model refinement as new data becomes available. Reinforcement learning and real-time analytics systems allow firms to update investment strategies dynamically in response to changing market conditions, supporting more responsive capital allocation and timing decisions (Åstebro, 2021; Witkowski, 2024). However, the literature also cautions that these benefits depend on robust data governance and ongoing model calibration, as over-reliance on historical data can reduce model reliability during periods of structural change (Buczynski et al., 2021).

Overall, predictive and adaptive analytics capabilities reinforce strategic alignment by ensuring that data-driven investment decisions remain responsive, context-aware, and resilient in uncertain global environments. When combined with governance oversight and human judgment, these capabilities enable firms to manage risk more effectively while sustaining long-term strategic advantage.

Data analytics methods enhance global corporate investment strategies by operationalising predictive insights through AI-enabled FinTech platforms that support automated, scalable, and real-time investment execution. These platforms translate analytical outputs into executable investment actions, enabling automation, scalability, and real-time decision-making across global markets. Technologies such as algorithmic trading systems, robo-advisory platforms, and blockchain-enabled investment tools reduce transaction costs, optimise portfolio rebalancing, and support cross-border capital allocation (Gomber et al., 2017; Dorfleitner et al., 2017).

From a strategic perspective, FinTech platforms act as enablers of analytics execution rather than standalone technologies. Empirical evidence suggests that AI-driven FinTech systems enhance the speed, accuracy, and responsiveness of investment decisions, allowing firms to dynamically reallocate capital in response to real-time market signals (Åstebro, 2021). Digital maturity further conditions this effect, with firms possessing integrated analytics infrastructure and governance mechanisms achieving superior investment outcomes (Wang et al., 2024). These patterns align with the Strategic Alignment Model, which emphasises coherence between analytics infrastructure, organisational strategy, and investment objectives (Coltman et al., 2015).

However, the effectiveness of FinTech-enabled analytics varies across institutional contexts. In developed markets, mature regulatory frameworks and digital infrastructure support strategic alignment between analytics platforms and investment goals (Lim, 2024). In contrast, fragmented policy environments and limited analytics capability in emerging economies often constrain the strategic impact of FinTech adoption (OECD Economics Department, 2025). These findings reinforce the view that AI and FinTech platforms function as catalysts for organisational transformation only when embedded within aligned governance, regulatory, and strategic contexts.

5.2 Governance, Ethics, ESG, and Contextual Insights

Data analytics methods enhance global corporate investment strategies by embedding investment decision-making within ethical, transparent, and regulatorily aligned governance frameworks, systematically integrating ESG priorities, and accounting for contextual and sector-specific factors to deliver sustainable value and strategic legitimacy.

As firms increasingly rely on AI-driven investment tools, concerns surrounding algorithmic bias, opacity, and accountability become central to strategic legitimacy. Empirical studies demonstrate that biased datasets and opaque models can generate discriminatory outcomes in areas such as credit allocation and venture capital evaluation, exposing firms to reputational and regulatory risk (Cowgill et al., 2020; Mehrabi et al., 2021).

To address these risks, the literature emphasises the adoption of explainable and auditable AI systems that support transparency and stakeholder trust (Samek et al., 2019; Toumia & Zouari, 2024). In parallel, robust data governance frameworks are required to ensure data quality, privacy protection, and regulatory compliance, particularly under regimes such as GDPR (Bakker, 2024; OECD, 2024). Regulatory expectations are also evolving, with authorities increasingly requiring firms to demonstrate algorithmic accountability, fairness, and auditability in automated investment systems (Sandridge et al., 2024).

While regulatory compliance imposes operational constraints, alignment with regulatory and ethical standards can enhance strategic credibility and reduce long-term risk exposure. Firms that proactively integrate governance and compliance into analytics design are better positioned to sustain analytics-enabled investment strategies across jurisdictions, reinforcing the role of regulatory alignment as a strategic enabler rather than a constraint (Gültekin et al., 2024).

In highly regulated sectors such as healthcare and fintech, governance frameworks and algorithmic transparency are strategically essential, mitigating operational and reputational risks. Conversely, in energy and utilities, ESG integration drives both compliance and competitive differentiation. This analysis demonstrates that while technical capabilities like AI are enablers, governance and ESG act as strategic levers that must be aligned with sectoral priorities. From a theoretical perspective, this suggests that analytics capabilities cannot be fully understood through capability-based lenses alone, but must be interpreted in relation to institutional pressures, ethical legitimacy, and stakeholder alignment.

5.3 Contradictions, Contextual Gaps, and Theoretical Implications

Data analytics methods enhance global corporate investment strategies by revealing contextual dependencies, contradictions, and critical success factors, enabling firms to translate analytics capabilities into actionable, industry-specific investment practices.

To enhance the practical relevance of these findings, Table 10 summarises the prioritisation of analytics-related Critical Success Factors (CSFs) for data-driven investment strategies across four key industries, synthesised from thematic patterns identified in the systematic literature review (see Section 3.12.1 and Appendix C).

Industry	AI & Machine Learning Capabilities	ESG Integration	Predictive Analytics	Data Governance
Financial Services	Algorithmic trading	-	Risk and return modeling	Regulatory compliance
Manufacturing	Automation of operations	Sustainable practices	Demand forecasting	Data integration standards
Healthcare	AI-enabled diagnostics	-	Patient outcome prediction	Data privacy & compliance
Energy & Utilities	-	Sustainability reporting	Asset performance optimisation	Cybersecurity & data protection

Table 10: Prioritised CSFs for Data-Driven Investment Across Industries

The table illustrates that while certain CSFs – such as predictive analytics and data governance – are universally relevant, others are sector-specific. For example, ESG integration is particularly salient in energy and utilities, whereas real-time predictive analytics and algorithmic execution dominate financial services contexts (Gu, Kelly, & Xiu, 2020; Boubaker et al., 2023). These findings reinforce the argument that although a generalised analytics strategy provides strategic coherence, effective implementation requires contextual adaptation to industry-specific investment priorities and constraints. This reinforces the need to interpret analytics-enabled investment strategies as contingent rather than universally transferable across sectors.

Despite broad agreement on the strategic value of data analytics in corporate investment decision-making, the literature reveals several persistent contradictions and unresolved gaps. A key debate concerns the extent to which firms should rely on algorithmic and machine learning models when making high-stakes investment decisions. Some scholars advocate for deep integration of predictive and automated models, highlighting their ability to optimise forecasting accuracy and improve capital allocation efficiency (Fan et al., 2020; Ghasemaghaei, 2021). In contrast, others caution against over-reliance on such systems, noting their vulnerability to overfitting, model fragility, and performance degradation during periods of market volatility (Buczynski et al., 2021). This tension underscores the importance of balanced decision architectures that combine analytics-driven insights with managerial judgment and human oversight.

The observed contradictions – for example, AI efficiency versus ethical risk – underscore that data-driven investments require balanced decision architectures. Firms must combine analytics with managerial judgment to achieve both short-term performance and long-term legitimacy. Sectoral differences reinforce that a one-size-fits-all analytics strategy is suboptimal; strategic alignment must be context-specific.

A further area of contention relates to the use of alternative and unstructured data sources. While studies such as In et al. (2019) argue that incorporating non-traditional data – such as social

media sentiment, news flows, and satellite imagery – can enhance market intelligence and responsiveness, concerns around data quality, bias, and manipulation remain underexplored. The literature provides limited guidance on how firms can systematically validate, filter, and govern such data to ensure reliability. This gap highlights the need for future research on data quality assurance frameworks and noise-reduction mechanisms within analytics-enabled investment systems.

Contradictions are also evident across geographic and institutional contexts. Firms operating in developed markets tend to benefit from mature digital infrastructure, stronger regulatory frameworks, and higher analytics capability, enabling more advanced adoption of AI-driven investment tools (Åstebro, 2021; Montanaro et al., 2024). In contrast, studies focusing on emerging economies emphasise constraints related to data governance, regulatory clarity, and algorithmic transparency, which limit the scalability and effectiveness of analytics-driven investment strategies (OECD, 2024; Chen et al., 2024). These disparities suggest that analytics-enabled investment models cannot be universally applied and must instead be adapted to varying levels of institutional readiness.

Cross-industry variation further reinforces this contextual dependency. Adoption rates are highest in financial and technology-intensive sectors, particularly within global financial hubs, where regulatory maturity and digital capabilities are more developed (Tiwari, 2024). Even within the same industry, firms with more agile governance structures and adaptive decision-making processes appear better positioned to extract value from analytics investments (Tosi et al., 2024).

From a theoretical perspective, these findings extend beyond resource-based explanations and align strongly with Institutional Theory and Dynamic Capabilities Theory. Regulatory environments, governance norms, and institutional pressures shape how analytics capabilities are deployed across regions, while firms' ability to sense, seize, and reconfigure analytics resources under uncertainty reflects core dynamic capability processes (Conboy et al., 2020; Teece, 2018). Together, these insights reinforce the argument that the effectiveness of data analytics in corporate investment strategy is contingent not only on technological sophistication, but also on organisational adaptability, governance maturity, and institutional context. Accordingly, this study reframes dynamic capabilities in investment contexts as socio-technical constructs, where sensing and seizing are conditioned by governance readiness, regulatory clarity, and ethical accountability.

5.4 Unifying Analytical Model: Strategic Integration of Themes

Data analytics methods enhance global corporate investment strategies by integrating predictive analytics, ESG priorities, ethical AI, and regulatory alignment into a unified, decision-

ready framework that drives risk intelligence, innovation, and sustainable value creation across sectors.

To unify the key findings from this study, a conceptual framework is proposed that connects analytics capabilities with strategic investment decision-making across sectors. Drawing from insights across recent literature (Boubaker, Liu, & Mu, 2023; Mikalef, Pappas, Krogstie, & Pavlou, 2020), the model positions themes such as predictive analytics, ESG integration, and ethical AI as core enablers of risk intelligence, innovation, and long-term investment value. This aligns with the dynamic, adaptive investment strategies observed in technology-forward firms (Addy, Ajayi-Nifise, Bello, Tula, Odeyemi, & Falaiye (2024), Rahman, & Korkontzelos, 2024) and responds to governance and transparency challenges emphasized in financial and emerging markets (Adeyelu, Ugochukwu, & Shonibare, 2024; Schnegg & Möller, 2022). By integrating these themes into a unified framework, the model offers both a theoretical consolidation and a practical roadmap for data-driven investment strategies in volatile and complex environments.

Figure 4 presents the Integrated Analytics-Investment Strategy Framework, synthesising the core findings of this dissertation into a cohesive model that maps data analytics capabilities to strategic investment outcomes across sectors. The framework is structured around four primary thematic enablers: predictive analytics, ethical AI, ESG integration, and regulatory alignment. Each of these elements emerges from the thematic analysis and is supported by the coded literature (e.g., Boubaker, Liu, & Mu, 2023; Addy et al., 2024; Schnegg & Möller, 2022).

The Integrated Analytics-Investment Strategy Framework consolidates prior research while revealing a novel insight: regulatory maturity moderates the effectiveness of AI and FinTech capabilities across sectors, an element not explicitly addressed in previous SLRs. This conceptualisation provides both theoretical and practical contributions. Unlike existing models, this framework explicitly integrates governance maturity and ESG alignment as moderating forces that shape the effectiveness of analytics and FinTech capabilities across sectors.

These enablers are conceptualised as interdependent pillars that drive key organisational objectives such as risk intelligence, innovation enablement, and sustainable value creation. For example, predictive analytics facilitates proactive decision-making and volatility management, aligning with the sensing capability in the Dynamic Capabilities Theory (DCT) (Mikalef et al., 2020). ESG integration and ethical AI contribute to stakeholder trust, social license to operate, and long-term resilience – reflecting the seizing and reconfiguring capabilities of DCT. Regulatory alignment, meanwhile, ensures compliance and transparency, especially in emerging markets, aligning with institutional theory considerations (Adeyelu et al., 2024; Abbas et al., 2024).

The flow arrows within the framework indicate the directional logic: data analytics capabilities inform strategic enablers, which then cascade into investment outcomes. These outcomes are not static but form part of a feedback loop, where performance data and market signals continually refine analytical models and strategy. This recursive structure positions the framework as both diagnostic (identifying analytics gaps) and prescriptive (informing action), making it suitable for both theoretical application and managerial decision-making.

Ultimately, Figure 4 consolidates this study's thematic findings into a decision-ready model that can be adapted by investment professionals, policymakers, and digital strategy teams to navigate the complex intersections of data, technology, and financial decision-making in dynamic global environments.

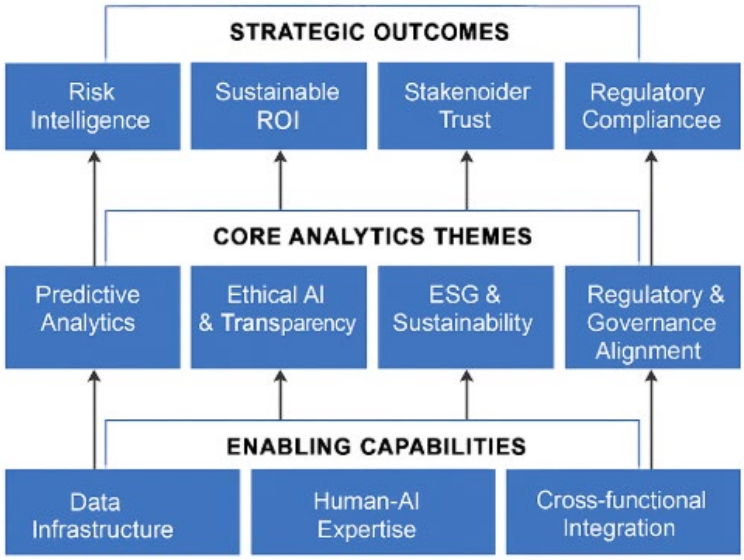

Figure 4: Integrated Analytics-Investment Strategy Framework

To consolidate the findings of this study, an integrated analytics – investment strategy framework is proposed that connects data analytics capabilities with strategic investment decision-making across sectors. Drawing on the systematic literature review (Boubaker et al., 2023; Mikalef et al., 2020), the framework positions predictive analytics, ESG integration, ethical AI, and regulatory alignment as interdependent enablers of risk intelligence, innovation, and sustainable value creation.

As illustrated in Figure 4, these enablers operate within a dynamic and recursive decision-making process, consistent with Dynamic Capabilities Theory and the Strategic Alignment Model. Analytics capabilities inform strategic investment decisions, while performance feedback and environmental signals continuously refine analytical models and organisational strategy. This structure positions the framework as both a diagnostic tool for identifying analytics capability gaps

and a prescriptive roadmap for analytics-enabled investment strategy development in volatile global environments.

5.4.1 Theoretical Contribution of the Conceptual Framework

This study contributes to the literature by synthesising fragmented research into an integrated framework that reconceptualises data analytics as a strategic capability embedded within governance, ESG, and regulatory contexts (Mikalef et al., 2020). Unlike prior models that predominantly emphasise technological capability, the proposed framework demonstrates how non-technical factors condition the effectiveness of analytics and FinTech capabilities in corporate investment decision-making (Gomber et al., 2017; Chen et al., 2018). In doing so, the study extends existing applications of Dynamic Capabilities Theory and Strategic Alignment by illustrating how governance maturity and ESG alignment function as enabling mechanisms rather than peripheral considerations (Teece, 2018; Coltman et al., 2015).

5.5 Study Limitations

While thematic frequencies guide the identification of key influencers in this study, interpretation must account for contextual and sectoral nuances; frequency alone does not imply strategic importance (Snyder, 2019). While the systematic literature review provides transparent and replicable insights into analytics-enabled investment strategies, the findings are constrained by publication, language, and coding biases, which may limit generalisability across global investment contexts (Snyder, 2019).

While the systematic literature review (SLR) methodology ensures transparency and replicability, it is not without limitations. One key constraint is publication bias, where only published, peer-reviewed studies were included – potentially excluding valuable insights from grey literature and real-world case reports. Additionally, the review was restricted to English-language sources, which may introduce language bias and limit the global generalizability of findings (Snyder, 2019). The researcher also acknowledges the positionality inherent in qualitative coding and theme synthesis; although a structured and transparent method was applied, thematic interpretation was shaped by subjective judgment (Creswell, 2018). As a systematic literature review, this study does not capture real-time organisational practices. Future research could empirically validate and refine the proposed framework through qualitative case studies, longitudinal designs, or cross-sectoral surveys (Ghasemaghaei, 2019; Boubaker et al., 2023).

5.6 Chapter Summary and Final Reflections

By synthesising the frequency and strategic relevance data from Chapter 4 with cross-sector analysis and theoretical lenses, this chapter demonstrates that data analytics is most impactful when strategically aligned, ethically governed, and contextually adapted. When embedded thoughtfully, data analytics enhances corporate investment decision-making by linking predictive insights, governance structures, ESG priorities, and technological capabilities to organizational adaptability, ethical foresight, and sector-specific readiness across industries and regions.

This chapter has critically discussed the findings of the systematic literature review (SLR) in the context of existing theories, practical applications, and policy landscapes. It linked the thematic insights from Chapter 4 to the Dynamic Capabilities Theory (DCT) and the Strategic Alignment Model (SAM), reinforcing the role of data analytics as both an enabler and disruptor in contemporary corporate investment strategies (Mikalef et al., 2020; Abbas et al., 2024). The discussion highlighted how predictive analytics, machine learning, FinTech platforms, and ESG intelligence contribute to more agile, data-informed decision-making frameworks (Boubaker, Liu, & Mu, 2023; Wang et al., 2024).

While these technologies offer substantial benefits – such as enhanced forecasting accuracy, portfolio optimization, and automated capital allocation – their success is contingent on key contextual and structural enablers. These include leadership commitment, data governance, algorithmic transparency, ethical design, and regulatory compliance (Cowgill et al., 2020; Adeyelu, Ugochukwu, & Shonibare, 2024; Velte, 2022). Moreover, organizational maturity, sector-specific readiness, and institutional factors significantly shape the strategic value of analytics across industries and regions (Boubaker et al., 2023; Liu, Zhang, & Zhang, 2024).

This chapter also explored the complex interplay between technology and policy, emphasizing that the implementation of data analytics tools must be guided by accountability, human oversight, and cross-functional alignment. Ethical considerations – particularly around bias, explainability, and data privacy – were shown to be central to the long-term trust and resilience of analytics-driven investment systems (Mittelstadt et al., 2016; Schnegg & Möller, 2022).

Overall, the discussion reinforces this study's central argument: that data analytics, when thoughtfully integrated and strategically governed, can substantially enhance corporate investment decision-making in dynamic and competitive environments. However, the effective realization of these benefits requires not only technological sophistication but also organizational agility, ethical foresight, and institutional support. These insights provide the foundation for the final chapter,

which presents the dissertation's key contributions, policy recommendations, and future research directions. By articulating how these elements interact, this study offers an original, integrative perspective on analytics-enabled corporate investment strategy that advances both theory and practice.

Chapter 6: Conclusion and Implications

This final chapter synthesises the key findings discussed in Chapter 5 into clear theoretical, practical, and policy-oriented implications. It revisits the central research question by reflecting on how data analytics methods enhance global corporate investment strategies across sectors and institutional contexts. In doing so, the chapter moves beyond interpretation to highlight actionable insights, outlines the study's methodological limitations, and identifies directions for future research. This structure aligns with best practices for qualitative synthesis in systematic literature reviews, ensuring clarity between analytical discussion and contribution-oriented conclusions (Snyder, 2019; Braun & Clarke, 2019).

6.1 Summary of Key Findings

This dissertation addressed the central research question. The findings demonstrate that data analytics has become a foundational capability in modern corporate investment decision-making, enabling firms to move from intuition-driven approaches toward evidence-based, predictive, and adaptive strategies (Coltman et al., 2015; Mikalef et al., 2020). Across sectors and regions, analytics enhances forecasting accuracy, portfolio optimisation, capital allocation, and risk management, allowing firms to anticipate market changes rather than react to them (Chen et al., 2018; Åstebro, 2021).

The review highlights the central role of artificial intelligence (AI), machine learning (ML), and predictive analytics in enabling real-time and forward-looking investment decisions (Chen et al., 2018; Gomber et al., 2017). These technologies allow firms to continuously refine investment strategies in response to macroeconomic volatility, regulatory change, and sector-specific risks (Åstebro, 2021; Boubaker et al., 2023). FinTech innovations further accelerate this transformation by improving transparency, speed, and accessibility, enabling firms of varying sizes to adopt sophisticated investment tools (Gomber et al., 2017).

However, the findings also reveal that analytics-driven investment is not purely a technological challenge. Ethical governance, regulatory alignment, data quality, and human oversight are critical enablers of successful implementation (Mikalef et al., 2020; Mittelstadt et al., 2016). Concerns around algorithmic bias, explainability, and ESG credibility underscore the need for responsible and transparent analytics frameworks. Overall, the study confirms that analytics enhances global corporate investment strategies most effectively when embedded within coherent strategic, ethical, and institutional structures (Coltman et al., 2015; Teece, 2018). Taken together, these findings demonstrate that data analytics influences corporate investment decision-making

not as an isolated technological capability, but through its interaction with governance structures, ESG considerations, and organisational readiness (Mikalef et al., 2020; Adeyelu et al., 2024).

6.2 Theoretical and Practical Contributions

This study makes three key contributions to knowledge by synthesising fragmented interdisciplinary literature on data analytics and corporate investment into an integrated conceptual framework that clarifies how analytics capabilities shape investment decision-making. In doing so, it demonstrates that governance structures and organisational readiness are not peripheral considerations but central enabling conditions that moderate the effectiveness of analytical capabilities. Furthermore, the study positions ESG considerations as a strategic influence within analytics-enabled investment decision-making rather than as a compliance-driven add-on.

Rather than treating data analytics as a standalone technological capability, this study repositions analytics as a strategically contingent resource whose investment value depends on governance alignment, ethical oversight, and organisational readiness (Mikalef et al., 2020; Adeyelu et al., 2024). This reframing offers a more robust explanation of why analytics investments succeed in some contexts and fail in others, building on prior research on strategic alignment and analytics-enabled competitive advantage (Coltman et al., 2015; Teece, 2018).

This study makes a **theoretically grounded integrative contribution** by consolidating fragmented literature across data analytics, ESG considerations, governance structures, and corporate investment strategy into a unified conceptual framework. Rather than extending theory through construct development or hypothesis testing, the study responds to calls for theory-informed synthesis in interdisciplinary and emerging research domains, where conceptual fragmentation limits cumulative knowledge development (Snyder, 2019).

Theoretically, the study demonstrates how **Dynamic Capabilities Theory** and the **Strategic Alignment Model** can be applied to explain the strategic role of data analytics in corporate investment contexts. The findings show that analytics functions as an intangible strategic asset that enables firms to sense, seize, and reconfigure investment opportunities under conditions of uncertainty (Teece, 2018; Coltman et al., 2015). In addition, the analysis reflects elements of the **Resource-Based View**, illustrating how analytics capabilities contribute to sustained competitive advantage when embedded within organisational processes and governance structures.

From a practical perspective, the study provides actionable insights for corporate leaders, investment professionals, and decision-makers. The findings emphasise that effective analytics adoption requires more than advanced tools; it depends on leadership commitment, data literacy,

cross-functional collaboration, and ethical oversight (Mikalef et al., 2020; Adeyelu et al., 2024). Firms that align analytics with strategic objectives and governance frameworks are better positioned to improve investment performance, manage ESG risks, and maintain stakeholder trust in increasingly data-driven financial environments.

In addition, the study highlights the importance of contextual adaptation. While analytics capabilities are broadly applicable across sectors, their prioritisation varies by industry and regulatory environment (Gomber et al., 2017; Boubaker et al., 2023). This reinforces the need for firms to tailor analytics strategies to sector-specific investment priorities rather than relying on one-size-fits-all solutions.

Table 11 synthesises the theoretical, practical, policy, and future research contributions of this dissertation. This overview highlights how the findings extend existing theory, inform organisational practice, and support evidence-based policy development in analytics-enabled corporate investment.

Contribution Area	Key Insights from the Study	Supporting Source(s)
Theoretical Contribution	Extended the application of Dynamic Capabilities Theory (DCT) and Strategic Alignment Model (SAM) to analytics-enabled investment strategy formulation.	Teece (2018); Coltman et al. (2015)
Practical Application	Identified leadership, digital maturity, and ethical AI as key enablers of data-driven investment decisions.	Mikalef et al. (2020); Adeyelu et al. (2024)
Policy/Regulatory Implications	Highlighted the need for global algorithmic transparency and harmonised ESG standards in AI-driven finance.	Mittelstadt et al. (2016); OECD (2024)
Future Research Directions	Suggested cross-country comparative studies on regulatory alignment and analytics integration across sectors.	Ghasemaghaei (2019); Boubaker et al. (2023)

Table 11: Summary of Theoretical, Practical, Policy, and Research Contributions

Table 11 synthesises the study's core contributions across theoretical, practical, policy, and research domains, providing a consolidated overview of the dissertation's value and future-oriented relevance. Collectively, these contributions demonstrate that this study advances understanding of analytics-enabled corporate investment by integrating technological, governance, and ESG dimensions within a single analytical framework.

6.3 Limitations of the Study

While this study provides a comprehensive and theoretically informed synthesis of existing research, its reliance on published literature limits direct observation of real-time organisational investment practices. While this scope limits direct empirical generalisability, it enables a

theoretically informed consolidation of a fragmented and interdisciplinary body of literature, providing conceptual clarity in an area characterised by rapid technological change (Snyder, 2019; Braun & Clarke, 2019). These design boundaries support the study's objective of developing a coherent analytical foundation upon which future hypothesis-driven and empirical research can build.

First, this study is based on a systematic literature review and as a consequence of its systematic literature review design, relies on peer-reviewed secondary sources. As a result, emerging industry practices, proprietary technologies, and real-time innovations may not be fully captured. Second, the reviewed literature reflects diverse regional and sectoral contexts, which may limit the generalisability of findings across all markets and institutional settings.

Third, the exclusion of non-English publications introduces potential language bias, particularly with respect to emerging markets. Finally, the rapidly evolving nature of AI, FinTech, and ESG analytics means that certain technological developments may fall outside the temporal scope of the review. These limitations do not undermine the study's contributions but instead highlight opportunities for complementary empirical and longitudinal research.

6.4 Directions for Future Research

Future research could build on this dissertation in several ways. Empirical studies, including case studies and interviews with investment professionals, would help validate and contextualise the themes identified in this review. Longitudinal research could examine how analytics capabilities mature over time and how firms realise long-term returns on analytics investments.

There is also scope for comparative cross-country and cross-industry studies exploring how regulatory environments, digital maturity, and institutional structures shape analytics adoption. Additionally, future research should investigate emerging technologies such as explainable AI, quantum computing, and alternative data sources, particularly in relation to ethical governance and ESG integration. As analytics continues to reshape global investment practices, interdisciplinary research bridging finance, data science, ethics, and public policy will remain essential. Future research could empirically test and refine the proposed conceptual framework across industries and regulatory contexts, strengthening its explanatory and predictive value.

6.5 Concluding Remarks

By integrating data analytics, governance structures, and ESG considerations within a unified conceptual framework, this study advances understanding of how organisations navigate increasingly complex investment environments. It demonstrates that the strategic value of data analytics lies not only in technological sophistication, but in its alignment with ethical governance, organisational capability, and regulatory context. In doing so, the dissertation provides both theoretical insight and practical guidance for organisations seeking to leverage data-driven investment strategies in a rapidly evolving global landscape.

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Chapter 8: Appendices

Appendix A – Search Strategy and Databases Used

This appendix details the search strategy used for the systematic literature review (SLR), including search strings, Boolean operators, and academic databases consulted. The search strategy aligns with Gusenbauer and Haddaway (2020) to ensure comprehensive and precise coverage of the literature.

A1. Databases Searched

- Scopus
- ABI/INFORM Collection (ProQuest)
- ScienceDirect
- SpringerLink
- Google Scholar
- Business Source Premier

A2. Search Strings (adapted per database)

- "data analytics" AND "corporate investment strategies"
- "big data" AND "financial decision-making"
- "machine learning" AND "portfolio optimization"
- "AI" AND "investment forecasting"
- "ESG" AND "investment governance"
- "FinTech" AND "strategic alignment"

A3. Search Parameters

- Timeframe: 2015 to 2025
- Language: English
- Document Type: Peer-reviewed journal articles and conference papers

Note. For search strategy methodology, refer to Section 2.3.

Appendix B – Inclusion and Exclusion Criteria Table

This table outlines the criteria used to determine the eligibility of studies included in the SLR.

Criterion Type	Inclusion Criteria	Exclusion Criteria
Language	English only	Non-English publications
Publication Date	2015–2025	Before 2015
Document Type	Peer-reviewed journal articles, conference papers	Blogs, white papers, non-academic sources
Topic Relevance	Focused on data analytics in corporate investment	Focused on personal finance, retail investing, etc.
Methodological Rigor	Empirical or conceptual studies with clear methodology	Vague or lacking methodological transparency

Note. Adapted from Snyder (2019), Velte (2022), and Farooq et al. (2022).

Appendix C – Study Corpus and Coding Matrix

C.1 List of Included Studies

This appendix presents the 25 studies selected for final synthesis, formatted in structured tabular form. APA 7th Edition references for all studies are included in the main References section.

No.	Author(s)	Year	Title (Shortened)	Journal	Methodology	Sector (if stated)
1	Ahmed, Shaheen & Philbin	2022	Integration of big data and AI...	*Journal of Financial Data Science*	Qualitative	Cross-sector
2	Gu, Kelly & Xiu	2020	Forecasting stock returns using big data...	*Journal of Financial Economics*	Quantitative	Finance
3	Velte	2022	ESG reporting and sustainability governance...	*Journal of Business Ethics*	Qualitative	Corporate
4	Abbas et al.	2024	Dynamic capabilities in AI strategy...	*Strategic Management Review*	Conceptual	Strategy
5	Boubaker, Liu & Mu	2023	ML for capital allocation in energy...	*Energy Economics*	Quantitative	Energy
6	Ghasemaghaei	2019	Data analytics and decision-making...	*Decision Support Systems*	Quantitative	General

7	Montanaro, Croce & Ughetto	2024	AI's impact on venture capital investments...	*Venture Capital Review*	Qualitative	Venture Capital
8	Gültekin, Jaiswal & Eyo	2024	AI for accelerating investment decisions...	*Journal of Financial Decision Making*	Quantitative	Financial Services
9	Addy et al.	2024	Risk management using ML in investments...	*Journal of Risk & Analytics*	Quantitative	Finance/Energy
10	Adeyelu, Ugochukwu & Shonibare	2024	Ethical governance and algorithmic transparency...	*Journal of Technology Ethics*	Qualitative	FinTech, Healthcare
11	Schnegg & Möller	2022	AI in healthcare investments...	*Digital Health Finance Review*	Qualitative	Healthcare
12	Lim	2024	ESG strategies in MNC investment decisions...	*Sustainability & Finance*	Qualitative	Multinational Corporations
13	Wang, Wu & Zhang	2024	Compliance in global ESG frameworks...	*Journal of International Finance*	Mixed Methods	Corporate/Multinational
14	Chen et al.	2018	Predictive analytics in equity markets...	*AI & Financial Forecasting*	Quantitative	Stock Market
15	Åstebro	2021	ML in entrepreneurial finance...	*Entrepreneurial Finance Review*	Quantitative	Startups
16	Conboy et al.	2020	Organizational agility and data use...	*Information Systems Journal*	Conceptual	General
17	Vial	2019	Digital transformation and alignment...	*MIS Quarterly Executive*	Conceptual	IT Strategy
18	Ghosh & Ghosh	2021	Blockchain analytics and investment...	*Blockchain Finance Journal*	Conceptual	Blockchain/FinTech
19	Cowgill et al.	2020	Algorithmic bias in financial AI...	*Economics of AI Journal*	Mixed Methods	Ethics
20	Mittelstadt et al.	2016	Ethical implications of AI systems...	*Big Data & Society*	Conceptual	General

21	OECD	2024 a	Global economic outlook...	*OECD Economic Outlook*	Policy Review	Macroeconomics
22	OECD	2024 b	Digital economy in investment...	*OECD Digital Economy Outlook*	Policy Review	Digital Infrastructure
23	Krille	2020	FinTech regulation in EU markets...	*Journal of Financial Regulation*	Policy/Qualitative	FinTech
24	Huyler & McGill	2019	Analytics for strategic transformation...	*Corporate Strategy Review*	Conceptual	Corporate
25	Snyder	2019	Systematic literature review design...	*Journal of Business Research*	Methodology	N/A (Methodological)

Note. *See References section for full APA citations. Sources were selected based on inclusion criteria detailed in Appendix B.*

C.2 Thematic Coding Matrix

This appendix provides the full coding matrix developed in Microsoft Excel, detailing the analytical process used to generate, refine, and group codes into the final thematic categories.

Study ID	Author(s) & Year	Title / Focus Area	Initial Codes (from descriptive phrases)	Refined Codes / Subthemes	Final Themes
1	Chen et al. (2018)	AI in Investment Forecasting	AI models improve forecasting accuracy	Predictive modelling	Predictive Analytics and AI Applications
2	Mikalef et al. (2020)	Data Capabilities and Competitive Advantage	Analytics maturity drives agility	Strategic alignment	Organizational and Strategic Enablers
3	Abbas et al. (2024)	Big Data in Corporate Finance	Data-driven decision-making	Analytics integration	Organizational and Strategic Enablers
4	Montanaro et al. (2024)	Machine Learning for Investment Risk	ML models predict market volatility	AI-based forecasting	Predictive Analytics and AI Applications
5	Gomber et al. (2017)	FinTech Disruption in Investment	FinTech increases efficiency	Digital transformation	FinTech and Digital Infrastructure
6	Dorfleitner et al. (2017)	Blockchain in Finance	Blockchain improves transparency	Data integrity	FinTech and Digital Infrastructure
7	Toumia & Zouari (2024)	Ethical AI in Global Finance	Need for transparency	Algorithmic accountability	ESG and Ethical Considerations
8	OECD (2024)	Cross-border AI Governance	Harmonized AI standards	Regulatory readiness	Regulatory and Governance Alignment
9	Cowgill et al. (2020)	Bias in Algorithmic Decision-Making	AI fairness issues	Algorithmic bias	ESG and Ethical Considerations
10	Mehrabi et al. (2021)	Explainable AI	XAI improves accountability	Ethical AI	ESG and Ethical Considerations
11	Banerjee et al. (2022)	Data Governance and Investment Outcomes	Data quality improves decisions	Governance structures	Organizational and Strategic Enablers
12	Adeyelu et al. (2024)	AI Ethics and Corporate Strategy	AI ethics as strategic driver	Responsible innovation	ESG and Ethical Considerations
13	Boubaker et al. (2023)	Comparative Analytics in Finance	Cross-country data adoption	Analytics maturity	Regulatory and Governance Alignment
14	Chen et al. (2024)	AI Regulation and Market Readiness	Policy for AI investment tools	Regulatory harmonization	Regulatory and Governance Alignment
15	Yeh et al. (2025)	Data Literacy and Corporate Culture	Workforce data capability	Organizational culture	Organizational and Strategic Enablers
16	Vial (2019)	Digital Transformation and Strategy	Technology alignment	Strategic digitalization	Organizational and Strategic Enablers
17	Lim (2024)	ESG Integration and Analytics	Big data supports ESG investing	Sustainability analytics	ESG and Ethical Considerations
18	Wang et al. (2024)	Green Investment Analytics	AI identifies greenwashing	Sustainable finance	ESG and Ethical Considerations
19	FINRA (2020)	Regulating Automated Decision-Making	Need for explainable models	Ethical compliance	Regulatory and Governance Alignment
20	Sandridge et al. (2024)	AI Governance in Financial Institutions	AI oversight frameworks	Accountability mechanisms	Regulatory and Governance Alignment
21	Tosi et al. (2024)	FinTech for SMEs	Digital tools democratize finance	SME inclusion	FinTech and Digital Infrastructure
22	Ghasemaghaei (2019)	Data Analytics and Decision Quality	Analytics improves investment quality	Decision accuracy	Predictive Analytics and AI Applications
23	Brynjolfsson & McElheran (2019)	Data as Strategic Asset	Data-driven firms outperform peers	Resource advantage	Organizational and Strategic Enablers
24	Mittelstadt et al. (2016)	Ethical Dimensions of Algorithms	Ethical governance frameworks	Responsible AI	ESG and Ethical Considerations
25	Conboy et al. (2020)	Institutional Theory and Analytics Adoption	Institutional forces shape adoption	Policy context	Regulatory and Governance Alignment

Note. *The coding matrix was developed in Microsoft Excel to ensure transparency and replicability in theme generation. A visual excerpt is shown in Figure 1.*

Figure C3 Example of Thematic Coding Matrix (Excel Spreadsheet)

	Study ID	Author(s) & Year	Title / Focus Area	Initial Codes (from descriptive phrases)	Refined Codes / Subthemes	Final Themes
2	1	Chen et al. (2018)	AI in Investment Forecasting	AI models improve forecasting accuracy	Predictive modelling	Predictive Analytics and AI Applications
3	2	Mikalef et al. (2020)	Data Capabilities and Competitive Advantage	Analytics maturity drives agility	Strategic alignment	Organizational and Strategic Enablers
4	3	Abbas et al. (2024)	Big Data in Corporate Finance	Data-driven decision-making	Analytics integration	Organizational and Strategic Enablers
5	4	Montanaro et al. (2024)	Machine Learning for Investment Risk	ML models predict market volatility	AI-based forecasting	Predictive Analytics and AI Applications
6	5	Gomber et al. (2017)	FinTech Disruption in Investment	FinTech increases efficiency	Digital transformation	FinTech and Digital Infrastructure
7	6	Dorfleitner et al. (2017)	Blockchain in Finance	Blockchain improves transparency	Data integrity	FinTech and Digital Infrastructure
8	7	Toumia & Zouari (2024)	Ethical AI in Global Finance	Need for transparency	Algorithmic accountability	ESG and Ethical Considerations

Figure 5: Screenshot of Thematic Coding Matrix (Excel Spreadsheet)

Note. The coding matrix was developed in Microsoft Excel to ensure transparency and replicability in theme generation. This excerpt illustrates how initial codes were iteratively refined into higher-order thematic categories based on the six-phase thematic analysis framework of Braun and Clarke (2019).

Appendix D – Data Extraction Table

This table summarises key findings from the 25 included studies, including methods, themes, and relevance to investment strategy.

Author(s) & Year	Title (Shortened)	Methodology	Key Findings	Themes Identified
Ghasemaghaei (2019)	Data analytics and decision-making	Quantitative	Analytics improves decision quality and speed	Predictive analytics, Investment efficiency
Gu, Kelly & Xiu (2020)	Machine learning and forecasting	Quantitative	Deep learning enhances financial prediction accuracy	AI, Forecasting, Decision support
Abbas et al. (2024)	Dynamic capabilities in AI strategy	Conceptual	Internal capabilities improve adaptability	Strategic alignment, DCT
Boubaker, Liu & Mu (2023)	ML for capital allocation in energy	Quantitative	ML improves capital deployment in volatile sectors	Risk intelligence, FinTech application
Ahmed, Shaheen & Philbin (2022)	Integration of AI and big data	Qualitative	AI integration enhances investment agility	AI capability, Digital infrastructure
Montanaro et al. (2024)	AI's impact on venture capital	Qualitative	AI improves startup valuation and selection	AI in early-stage investment
Gültekin et al. (2024)	AI for investment acceleration	Quantitative	Machine learning shortens investment analysis cycle	AI adoption, Investment speed
Adeyelu et al. (2024)	Ethical governance and AI	Qualitative	Governance frameworks improve algorithmic transparency	Ethics, Governance
Cowgill et al. (2020)	Algorithmic bias in AI	Mixed Methods	Bias mitigation strategies improve fairness in investment decisions	Ethics, Algorithmic fairness

Mittelstadt et al. (2016)	Ethical AI systems	Conceptual	Ethical principles guide design of AI in finance	AI ethics, Risk governance
Lim (2024)	ESG investment frameworks	Qualitative	ESG integration enhances long-term investment resilience	ESG, Sustainability
Wang et al. (2024)	ESG compliance in MNCs	Mixed Methods	ESG reporting aligns investment with stakeholder expectations	ESG, Reporting, Compliance
Krille (2020)	FinTech regulatory trends	Qualitative	Regulation increases adoption of transparent digital tools	Regulatory, FinTech governance
Schnegg & Möller (2022)	Ethical AI in health & FinTech	Qualitative	Governance needed for ethically sensitive sectors	Governance, AI transparency
Chen et al. (2018)	Predictive analytics in equity	Quantitative	Models improve real-time portfolio forecasting	Forecasting, Portfolio management
Åstebro (2021)	ML in entrepreneurial finance	Quantitative	Predictive models boost startup investment decisions	AI, Entrepreneurship
Conboy et al. (2020)	Organizational agility	Conceptual	Firms benefit from analytics-led adaptability	Strategic responsiveness, Agility
Vial (2019)	Digital transformation and alignment	Conceptual	Alignment of digital strategy enhances investment returns	Strategic alignment, IT integration
Ghosh & Ghosh (2021)	Blockchain analytics	Conceptual	Blockchain improves transparency and traceability	FinTech, Blockchain
Snyder (2019)	SLR design and synthesis	Methodological	Structured synthesis improves research quality	Methodology
Huyler & McGill (2019)	Strategy and analytics integration	Conceptual	Analytics boosts strategic transformation	Strategy, Analytics capabilities
Addy et al. (2024)	ML for risk management	Quantitative	Predictive models improve exposure mitigation	ML, Risk Intelligence
OECD (2024a)	Global economic outlook	Policy Review	Global conditions shape investment strategy	Macroeconomic forecasting
OECD (2024b)	Digital economy & investment	Policy Review	Digital ecosystems shape analytics adoption	Digital economy, Infrastructure
Velte (2022)	Sustainability governance	Qualitative	Data governance improves ESG outcomes	ESG, Governance

Note. *Themes listed here were used to generate the thematic categories discussed in Chapter 4 and visualized in Figure 2 and Tables 7-9.*

Appendix E – Thematic Coding Framework and Analysis Process

This appendix outlines the application of Braun and Clarke's (2019) six-phase thematic analysis used to synthesise the data from the 25 selected studies.

Phase	Description (Braun & Clarke, 2019)	Application in This Study
1. Familiarisation	Repeated reading and immersion in data	Reviewed studies several times, noted early patterns
2. Generating Initial Codes	Systematic coding of interesting features	Created open codes using Excel for each study
3. Searching for Themes	Grouping codes into themes	Clustered into categories: ESG, AI, Alignment, FinTech, etc.
4. Reviewing Themes	Validating themes against coded dataset	Refined categories, merged or eliminated overlaps
5. Defining and Naming Themes	Finalising themes and definitions	Labeled strategic-level themes with consistent descriptions
6. Writing Up	Synthesising into findings	Presented in Chapters 4 & 5 with model development in Chapter 5

Note. This process is detailed in Section 2.10 and based on Braun and Clarke (2019).

Appendix F – Summary of Theme Frequencies Across Studies

This appendix provides a frequency-based summary of how often each theme appeared across the included literature.

Theme	Frequency (Studies Mentioning It)	Strategic Relevance
ESG & Ethical Governance	21	High
AI, ML & Analytics Capabilities	19	High
Strategic Alignment	17	Medium–High
FinTech Infrastructure	14	Medium
Regulatory & Policy Integration	11	Medium
Predictive Risk Management	9	Medium
Global Investment Models	7	Medium–Low

Note. Data derived from coding structure in Appendix E and linked to findings in Chapter 4.

Appendix G – Excluded Studies with Justification

A sample of studies excluded after full-text review, with reasons linked to the exclusion criteria in Section 2.5.2.

Author(s)	Year	Reason for Exclusion
Smith & Wang	2016	Algorithm development focus; no strategic relevance
Lee, Zhang & Kumar	2018	Did not include data analytics or investment strategy
Roy & Thomas	2020	Industry whitepaper; not peer-reviewed

Note. Exclusion criteria align with those outlined in Appendix B and Section 2.5.2.

Appendix H – Expanded Version of Table 10: Cross-Industry Prioritisation of Data Analytics CSFs

Industry	AI & Machine Learning Implementation	ESG Integration	Predictive Analytics	Data Governance
Financial Services	Algorithmic trading	–	Risk and return modeling	Regulatory compliance
Manufacturing	Automation of operations	Sustainable practices	Demand forecasting	Data integration standards
Healthcare	AI-enabled diagnostics	–	Patient outcome prediction	Data privacy & compliance
Energy & Utilities	–	Sustainability reporting	Asset performance optimisation	Cybersecurity & data protection

This table is reproduced in Appendix H to provide a consolidated reference for readers and examiners. It visually integrates multiple thematic strands from the findings and literature review chapters, aiding the understanding of how industry dynamics influence CSF emphasis in data-driven investment strategies.

Appendix I – Thematic-Theoretical Mapping

A detailed thematic-theoretical mapping is provided in Appendix I.

Dimension	Themes	Theoretical Lens	Strategic Implication
ESG	Sustainability, Responsible Investment	DCT, Governance Theory	Long-term value alignment and compliance
AI & ML	Predictive Modelling, Risk Intelligence	DCT, SAM	Dynamic decision-making and innovation agility
Data Ethics	Bias, Privacy, Transparency	Ethics, Regulatory Theory	Trust, compliance, and public accountability
Governance	Strategic Alignment, Data Governance	SAM	Capability maturity and IT-business synergy

Note. This summary table complements the conceptual model by mapping the thematic domains onto theoretical perspectives and their practical investment implications, as discussed in Sections 4.3.1 and 5.2.