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AI-BASED DECISION SUPPORT FOR OPTIMIZING SINGLE-STOCK INVESTMENT DECISIONS

Doctoral (PhD) dissertation

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Dissertation to obtain a PhD degree

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Prepared by the University of Sopron
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within the framework of the Business Economics & Management Program

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FORMULA AND LIST OF SYMBOLS

Formula/Symbol	Declaration
A	Set of all possible algorithms
I	- Investor (Principal): Represents the principal in Principal-Agent Theory; primarily used in early sections (e.g., Problem Identification). - Input Tuple (P, ISIN): Represents the input for downstream analysis; primarily used in later sections (e.g., Input and Data Analysis Layers).
F	Company (Agent)
V	Company Value
V_F	True Company Value (known by Company F)
V_I	Estimated Company Value (by Investor I)
SI	Signals (Information received by Investor)
$E[V_F \mid SI]$	Expected value of V_F given S ($V_I = E[V_F \mid SI]$)
ΔI	Information Asymmetry ($\Delta I = I_F \setminus I_I$)
I_I	Investor's Information Set
I_F	Company's Information Set
P	- Price of a Share: Represents share pricing in information asymmetry models; primarily used in early sections (e.g., Problem Identification). - Overall risk preference ($P = \min\big(C(S_t), C(S_w)\big)$) Represents investor risk profiling; primarily used in later sections (e.g., Input and Data Analysis Layers).
Ω-Knowledge	Theoretical Knowledge (e.g., Principal-Agent Theory)

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λ-Knowledge	Design Knowledge (e.g., AI and Data Science Models)
$f(SI)$	Function reflecting investor's interpretation of signals for price P
ϵ	Mispricing ($\epsilon = V_F - P$)
$\mathcal{M}$	Method or algorithm (selected from A)
R_t	Risk Tolerance
R_w	Risk Willingness
s_i	Indicator Value for Question i ($s_i \in \{1, 3, 5\}$)
S_d	Score for Dimension d (Risk Tolerance or Willingness, $S_d = \sum_{i=1}^{n} s_i$, $d \in \{t, w\}$)
$S_d^{\min}$	Minimum score for dimension d (5)
$S_d^{\max}$	Maximum score for dimension d (25)
$C(S_d)$	Category for Dimension d ($risk\ averse, if\ 5 \leq S_d \leq \tau_1, risk\ neutral, if\ \tau_1 < S_d \leq \tau_2, risk\ seeking, if\ \tau_2 < S_d \leq 25$)
τ_1	Threshold for classification (12)
τ_2	Threshold for classification (18)
$f(P, D)$	Downstream Analysis Function ($f: P \times D \rightarrow \mathcal{I}$)
D	Additional Investor Attributes (e.g., $ISIN$)
DS	Set of Data Sources
DS_i	Data Sources (e.g., LSEG, Reddit, Web)
DS'	Expanded Set of Data Sources (S' = σ_{search}(D$S, ISIN$)
σ_{search}	Search Function for Additional Web Sources
P_i	Access Parameters (e.g., API Keys, URLs)

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r_i	Retrieval Mechanisms (e.g., API Queries)
D_i	Retrieved Datasets
K	Set of Analysis Categories (e.g. fundamental data, sentiment analysis, risk metrics, hedging results, performance metrics and ESG data)
D_k	Categorized datasets ($D_k = \alpha_k(\{D_i\})$)
α_k	Aggregation Logic for Category k
C_k	Category-specific Criteria
S_k	Individual Score for Category k ($S_k = \beta_k(D_k, C_k)$)
β_k	Scoring Logic for Category k
S_{total}	Total Score (Weighted Sum of Category Scores, $S_{total} = \sum_{k \in K} w_k \times S_k, \sum_{k \in K} w_k = 1$
w_k	Weights for Category k
A_k	Agents for each Category k
O_k	Category-specific Outputs ($O_k = \gamma_k(D_k, S_k, C_k, P)$)
γ_k	Processing Function for Category k
R	Report ($R = LLM(\{O_k\}_{k \in K}, S_{total}, P, ISIN, \theta)$)
θ	LLM Configuration
R_{PDF}	Investment Report in PDF Format ($R_{PDF} = \phi(R)$)
ϕ	PDF Formatting Function
$1 - \alpha$	Confidence Level in VaR (α as Risk Level)
μ	Mean Return (EGARCH Model Parameter)
ω	Baseline Volatility (EGARCH Model Parameter)
$\alpha[1]$	ARCH Effect (EGARCH Model Parameter)

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$\gamma[1]$	Asymmetry Effect (EGARCH Model Parameter)
$\beta[1]$	Persistent Volatility Effect (EGARCH Model Parameter)
ν	Fat-tail Parameter (EGARCH Model Parameter)

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ABBREVIATION LIST

Abbreviation	Declaration
AI-DSS	AI-based Decision Support System
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average
bca	Bias-Corrected and Accelerated (Bootstrap)
BERT	Bidirectional Encoder Representations from Transformers
CI	Confidence Interval
CITC	Corrected Item-Total Correlation
DSR	Design Science Research
DSS	Decision Support System
EGARCH	Exponential Generalized Autoregressive Conditional Heteroskedasticity
ESG	Environmental, Social, and Governance
ETF	Exchange Traded Fund
FAISS	Facebook AI Similarity Search
FinBERT	Financial Bidirectional Encoder Representations from Transformers
FX	Foreign Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
HTTP	Hypertext Transfer Protocol
IoT	Internet of Things
ISIN	International Securities Identification Number
JSON	JavaScript Object Notation

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LLM	Large Language Model
LSEG	London Stock Exchange Group
MAD	Median Absolute Deviation
MAS	Multi-Agent System
MiFID II	Markets in Financial Instruments Directive II
ML	Machine Learning
NLP	Natural Language Processing
NN	Neural Network
PAT	Principal Agent Theory
RAG	Retrieval Augmented Generation
REST	Representational State Transfer
SERP	Search Engine Results Page
VaR	Value-at-Risk

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ABSTRACT

This thesis investigates and solves the related problem with information asymmetries in financial markets applying the Principal-Agent Theory (PAT) by developing an AI-based Decision Support System (AI-DSS) for single-stock investments. The challenge arises from investors' limited access to reliable data and varying interpretations in analyst reports, leading to mispricing and inefficient decisions. Using Design Science Research (DSR), the thesis elaborates on a fundamental research question about how AI-DSS supports risk-based decisions by the hypothesis that AI-DSS reduces information asymmetries through targeted data analysis.

Objectives include determining investor risk preferences per Markets in Financial Instruments Directive II (MiFID II, an EU regulation requiring financial institutes to assess client suitability and risk profiles). Further objectives are analyzing specific stocks via ISIN, generating tailored reports with financial, technical, and sentiment analyses, and enhancing decision-making by minimizing discrepancies between perceived and true company values.

The AI-DSS was evaluated through methodological triangulation, combining a framework analysis of 11 professional investment reports with an expert questionnaire of 18 financial professionals. The framework analysis yielded an average qualitative score of 4.35 out of 5, outperforming traditional reports (2.22) in transparency, risk adjustment, analytical relevance, and efficiency. These strengths stem from the system's use of EGARCH volatility modeling and NLP-based sentiment analysis across heterogeneous data sources (e.g., Reddit, LSEG APIs).

The expert questionnaire confirmed these results quantitatively with an aggregate score of 4.07 out of 5, supported by high internal consistency (α = 0.79–0.84; Ω = 0.83–0.92) and 100% CI overlap across bootstrap iterations, evidencing strong reliability. Together, the findings validate the hypothesis that AI-based DSS effectively reduce information asymmetries by aligning firm and investor value perceptions (V_F and V_I). Overall, the evaluation confirms the analytical robustness and practical utility of the AI-DSS, while limited data availability suggests potential for further expansion and broader adoption.

Keywords: Financial Markets, Investments, Information Asymmetries, Artificial Intelligence, Decision Support System, Principal Agent Theory, Design Science Research

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1 INTRODUCTION

This thesis applies the problem of information asymmetries between a principal and an agent, as outlined by the Principal Agent Theory (PAT), to the financial market (Shah, 2014). An AI-based decision support system (AI-DSS) will be implemented to resolve the information asymmetries between the two parties. In the context of PAT, an AI-DSS can help a retail, semi-professional, or professional investor to make a decision based on different high-quality data sources and scientific analysis.

1.1 Problem Identification and Motivation

Investing in a single stock requires a thorough analysis of the company. Investors must ensure that the stock aligns with their risk preferences by performing fundamental, technical, or individual risk assessment analyses to determine the company's intrinsic value. In this context, reliable information is crucial but often limited (Batool et al., 2024). Moreover, different investment reports written by investment agencies can create investment bias due to their varying interpretations (Devos, 2014; Mokoaleli-Mokoteli et al., 2009; Pursiainen, 2022). Furthermore, investors' limited knowledge of relevant key performance indicators or risk ratios of a given company can affect their decisions. These information gaps can ultimately lead to suboptimal investment decisions and potential misallocation of capital.

The thematic relevance of this research thesis arises from the continuing importance of information asymmetries on financial markets representing a key challenge for individual and institutional investors (Shah, 2014). These asymmetries impair the efficiency of investment decisions and increase the risk of mispricing. The development of an AI-DSS aims to close this information gap and improve decision-making. Formally, this can be represented as follows: in the free market, there are two players: an investor (I) and a company (F), the issuing company. Both assess the company value (V), but on different bases. Company F knows the "true" company value $V_F = E[\, V \mid I_F \,]$, , while investor I only receives the signals (SI) and estimates the value $V_I = E[\, V \mid I_I \,]$ based on them. This leads to an information disadvantage for I, which can cause an unexpected risk in investment decisions. In the ex-ante view, $V_F \neq V_I$ is generally assumed, as I_I does not include all the information available to the firm.

The information asymmetry arises because the investor's information set I_I is a genuine subset of the company's information I_F set $I_I \subset I_F$. The asymmetry can be modeled as $\Delta I = I_F \setminus I_I$, whereby a larger ΔI indicates a stronger asymmetry. The price of a share P is determined on the basis of the signals SI, which constitute the investor's information set I_I, i.e., $P = f(I_I)$, whereby f reflects the investor's interpretation of the signal. Due to the information asymmetry, the true company value V_F can deviate significantly from the price P, which causes a mispricing $\epsilon = V_F - P$. The objective is to minimize epsilon based on the functional $\min_{\mathcal{M} \in A} E\,[|V_F - V_I(\mathcal{M})|]$. The aim of the thesis is to minimize the information asymmetry ΔI by means of an AI-DSS. To this end, a method $\mathcal{M} \in A$, where A represents the set of possible algorithms, is used to minimize the expected absolute deviation between V_F and $V_I(\mathcal{M})$.

The company's limited signals, which only share a subset of their available information, constrain this process. Existing approaches to reducing information asymmetries often focus on isolated technologies or partial aspects, while a holistic model that integrates the needs of investors with different risk profiles is lacking (Koshiyama et al., 2020; Kruse et al., 2019). The ongoing digitalization of financial markets and the availability of real-time data reinforce the need for such a model.

The proposed AI-DSS addresses this gap by reducing the information asymmetry described in the modeling (ΔI) and promoting transparency and efficiency in the investment process. Theoretically grounded in PAT, which describes the conflict between investor (I) and company (F), the research is both academically and practically relevant. It develops an innovative system that meets real stakeholder needs and contributes to the optimization of capital allocation.

The present research employs a DSR approach to assess whether an AI-DSS can reduce information asymmetries between investors and companies behind a stock. The thesis is guided by two main research questions and one formal hypothesis, following common DSR processes. The research questions are:

> **RQ1:** Whether an AI-based DSS support investment decisions based on investors' risk willingness?
>
> **RQ2:** Which technological components are crucial for providing customized information on individual securities regarding information asymmetries?

The hypothesis is: "AI-based DSS reduce information asymmetries (ΔI) by analyzing data in a targeted manner and minimizing the discrepancy between V_F and V_I."

These questions and the hypothesis focus the AI-DSS research project on reducing information asymmetries and supporting individual investment decisions. The selection of two research questions and one focused hypothesis is consistent with established and pragmatic DSR logic (Hevner, 2007). DSR is not primarily a hypothesis-testing paradigm but emphasizes problem relevance, artefact construction, and rigorous evaluation (Elragal & Haddara, 2019; Hevner, 2007). Accordingly, the number of hypotheses is not a quality criterion in DSR; central requirements are relevance and rigor (Hevner, 2007; Kotzé et al., 2015). Prior analyses of n=104 DSR publications further show that projects may even proceed without formal hypotheses (Hoang et al., 2019; Kotzé et al., 2015). Against this background, two precise research questions and a single testable hypothesis provide an appropriate and methodologically sound structure for this thesis.

1.2 Objectives of the AI-DSS

Biases often influence investment decisions, making achieving a minimum variance portfolio difficult. One key factor for unbalanced investments is the presence of information asymmetries between companies and individual stock investors (Batool et al., 2024; Hatchondo, 2008). These asymmetries may result from limited access to reliable and comprehensive data, as well as complex financial metrics that can be challenging to analyze and interpret (Batool et al., 2024; Dziuda & Mondria, 2012; Hatchondo, 2008). Additionally, investment reports from various agencies may differ in their interpretations of similar KPIs due to different biases, information bases, and data availability. This issue affects both institutional and retail investors alike.

This research aims to address these challenges by implementing an AI-DSS for single stock investments, utilizing the DSR approach. Defining solution objectives is crucial within the DSR process to guide the implementation of the artifact. Consequently, a thorough problem statement analysis is essential to develop practical objectives.

The challenge of information asymmetries lies in accessing data stores and interpreting the data based on individual risk preferences. Retail and institutional investors may not have the resources or expertise to analyze complex financial reports, consider various qualitative and quantitative factors, and dedicate time to conduct thorough analysis for each investment decision. The AI-DSS aims to address these issues by providing personalized, transparent, and actionable information to enhance decision-making when investing in single stocks.

To address informational asymmetries between investors and companies, several key objectives must be considered. These objectives were established by experts in the financial industry. Consequently, some investment reports were provided to a specific target group. Each professional provided feedback on their requirements for an unbiased and individualized investment report. The DSR process will assess the following key objectives, which form the foundation of AI-DSS development.

1. Determination of Investor Risk Preferences

   Firstly, the determination of risk preference is required. National regulations, such as MiFID II (Markets in Financial Instruments Directive II), necessitate assessing an investor's financial background, knowledge and investment horizon through specific questions (Gortsos, 2018; Kümmerle & Conen, 2018). This assessment is necessary to develop an AI-DSS for personalized investment decisions. Therefore, identifying the investor's risk preference can be a primary objective in developing an AI-DSS to support investment decisions, addressing RQ1 on providing information customized to individual needs. By incorporating standardized questions, the system aligns with regulatory compliance while enabling individual analysis.

2. Analysis of specific Stocks

   Secondly, while the problem statement addresses information asymmetries between a company and an investor, the analysis focuses on single stock investment decisions. Therefore, it is crucial to determine which specific company requires analysis, in addition to considering risk preferences. In line with this objective, RQ2 will be addressed by providing relevant information pertaining to the selected stock. This ensures that the system concentrates on the stock chosen by the investor, thereby reducing the complexity associated with analyzing data from multiple companies.

In summary, the risk preference and the stock identifier are defined as input objectives for this research project. The AI-DSS must utilize these variables to reduce information asymmetries based on the specified risk preference and ISIN (International Securities Identification Number). These variables are specific and pertinent to addressing informational asymmetries in single stock investment decisions, while also connecting to regulatory requirements to enhance practical relevance.

Next to the presented input objectives, there are two more objectives guiding the research project:

3. Generate Tailored Investment Reports

   The AI-DSS aims to generate an investment report that simplifies complex financial ratios into actionable insights based on the investor's risk preference. This objective addresses the need for clear, concise information that helps investors make informed investment decisions and reduces information asymmetries. The AI-DSS will present stock-related information to enhance the decision-making process for investors. Using technologies like APIs, web scraping, machine learning algorithms, and generative AI, the system will create an investment report that provides useful information based on these sources. This system will synthesize key stock data into insights tailored to the individual's risk profile.

4. Enhance the investor decision-making process by reducing information asymmetries

   The report will take a general approach to address most investors' preferences by aggregating key data from various techniques and perspectives. It will have a clear layout with parts about financial performance, stock performance, and other important aspects like sentiment analysis and analyst recommendations; a thorough risk assessment; and a grading system to show how well it matches the investor's risk profile. The report will feature a grading system that summarizes the information into a score, indicating whether the investment matches the investor's risk preference. The goal of the AI-DSS is to reduce information asymmetries by providing and interpreting data according to individual risk preferences.

The developed AI-DSS will provide investors with a comprehensive information base upon receiving input variables such as risk preference and ISIN.

The four objectives are defined qualitatively and quantitatively and are derived from the problem definition and the PAT, as described in Section 1.1. In summary, the aim is to develop an AI-DSS that:

- Investors based on their risk willingness and the ISIN (RQ1).
- Technologies such as AI, web scraping, and statistical models are integrated to provide customized information (RQ2).
- Information asymmetries are reduced through targeted data analysis (hypothesis).

1.3 Structure of the Thesis

The thesis is structured into six chapters as depicted in Figure 1. The first chapter provides an overview of the problem identification and the significance of the research. It details the motivation for minimizing information asymmetries in single stock investment decisions, highlights the existing research gap, and presents the research questions (RQ1 and RQ2) along with the previously mentioned hypothesis. Subsequently, the objectives of the AI-DSS solution are examined, which directly address the identified problem and research questions. These objectives lay the foundation for the DSR approach applied throughout the thesis.

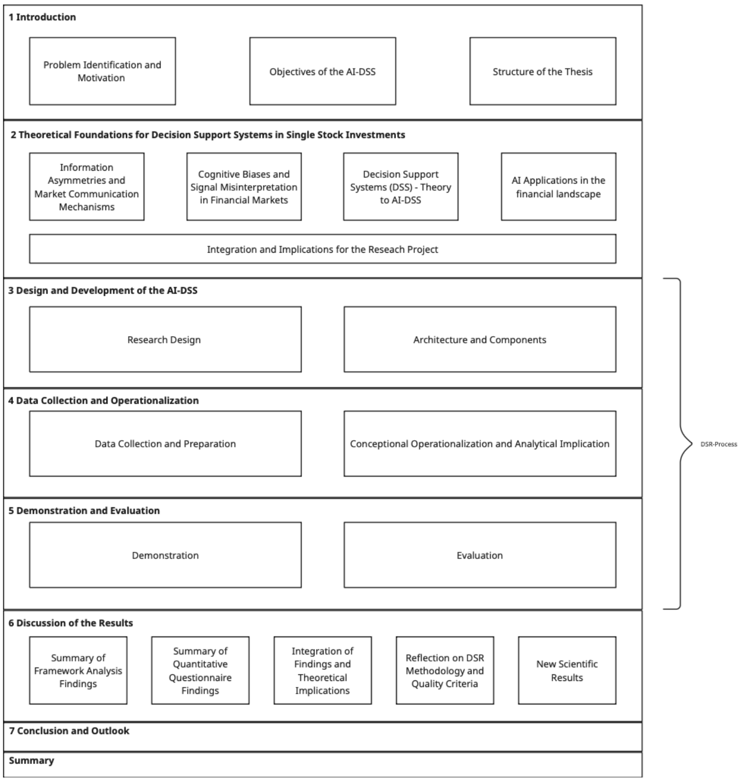

Figure 1: Structure of the Thesis

Source: own elaboration

The subsequent Chapter 2 provides an overview of existing theories pertinent to the research questions and hypothesis. Specifically, the Principal-Agent Theories are examined alongside Behavioral Finance and Investment Decisions. These two sections establish the foundation of the theoretical framework for this thesis. The chapter concludes with a description of DSS and their contextualization in finance. Following these sections, the application of AI in finance is contextualized, detailing the current research and development of AI tools within the financial sector. In summary, the theoretical foundations are reviewed, with particular attention given to their integration and relevance to the research project.

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Building upon these insights, the following chapter 3 presents the design and development of the AI-DSS. This chapter details the research design methodology and its practical application within the project, establishing a foundation for the subsequent architecture and component design, which is organized into four distinct layers. This architectural design establishes the basis for the subsequent chapter, which covers data collection and operationalization. The chapter outlines the phases of data retrieval, operationalization, data preparation, and analytical components and their integration within the AI-DSS. According to the research design of DSR, the demonstration and evaluation of the AI-DSS are followed by a detailed description of the demonstration process and the methodological triangulation used in the evaluation (including qualitative framework analysis and a quantitative expert questionnaire).

The two evaluations are performed independently, establishing a foundation for a multi-sided assessment that meets research quality standards and considers the DSR methodology. From these validated findings, the following new scientific results are formulated (Chapter 6). The thesis concludes with a discussion summarizing main findings and suggesting directions for future research in the final chapter.

2 THEORETICAL FOUNDATIONS FOR DECISION SUPPORT SYSTEMS IN SINGLE STOCK INVESTMENTS

This chapter presents the theoretical foundations and reviews the current state of research across four sections, where PAT (Jensen & Meckling, 1976; Pratt & Zeckhauser, 1985; Ross, 1973) is used as the theoretical basis for information asymmetries: the first section defines the origins and basic theories of PAT and its relevance for the financial market. Since PAT serves as the basis for this work, a detailed examination is necessary. After describing the fundamentals of PAT, a discussion of behavioral finance and investment decisions is presented in the subsequent section (Section 2.2). Further the role of DSS in a traditional and modern way will be declared. Subsequently, in Section 2.3. The applications of AI in finance will be presented through a historical timeline of AI developments, along with an overview of research on AI applications in areas such as risk management and asset management (Section 2.4). In the final chapter, these findings are brought together in the context of current perspectives for DSS in finance and current research projects. Thereby this chapter addresses this question by outlining the theoretical foundations for the thesis project aimed at developing an AI-DSS to reduce information asymmetries ($\Delta I = I_C \setminus I_I$) between investors (principal, I) and companies (agent, F) in single stock investments. The goal is to minimize the discrepancy between the investor's estimated value (V_I) and the true company value (V_F) ($E[\mid V_F - V_I \mid]$), thereby preventing mispricings ($P \neq V_F$).

2.1 Information Asymmetries and Market Communication Mechanisms

This chapter will examine the economic theories relevant to the research topic. PAT will be introduced first as the foundational theory, followed by a discussion of signaling theory in the subsequent section.

2.1.1 Information Asymmetries and Agency Conflicts in Investment Decisions

The PAT addresses the issues that arise due to the separation of ownership and control. To illustrate how PAT influences the investment process, this theory will first be briefly reviewed and then applied to the problem statement introduced in the previous section.

The initial assessment of the Principal–Agent problem can be traced back to Adam Smith's observation that directors of joint-stock companies, managing other people's money rather than their own, tend to exercise less diligence and vigilance compared to partners in private enterprises who are personally financially invested (A. Smith, 1776). This early insight provides a qualitative basis for future research. Building on this, a study analyzes the distinction between ownership and management, creating conditions where the objectives of owners may not align with those of managers The study ultimately concludes that, in many cases, a manager's interests do diverge from those of the owner (Berle & Means, 1932). These two studies can be highlighted as the starting point of the PAT; even then, the PAT was not formalized. The first formal elaboration occurred forty years later in a study that highlighted the distinction between owners and managers. The study described a situation in which a principal appoints an agent to provide services on their behalf and delegates decision-making authority to the agent (Pratt & Zeckhauser, 1985; Ross, 1973). This foundational concern was later substantiated by research indicating that corporate executives might prioritize personal objectives over shareholder value maximization (Bhabra & Wood, 2014; Jensen & Meckling, 1976; Tilton et al., 2023).

A review of the above-named studies indicates that PAT functions are based on two distinct roles and inherent information asymmetries:

- The principal is defined as the party delegating authority to an external agent. Business owners, shareholders, or investors typically assume this role, entrusting their capital to corporate management. Within the financial market context, this often refers to the classical investor (Jensen & Meckling, 1976; Ross, 1973; Shah, 2014).
- The party that receives authority from the principal is referred to as the agent. Agents are typically managers or executives who have operational control but may not always share the same objectives as the principal. According to qualitative literature, one reason for the distinction is that the agent holds only limited liability for their actions (Berle & Means, 1932; Jensen & Meckling, 1976; Pratt & Zeckhauser, 1985). In the context of financial markets, this term typically refers to the company that issues a particular stock.

Principal-agent relationships are defined by information asymmetries, where one party has more or better information. These asymmetries can take the form of hidden action, in which the principal cannot directly observe the agent’s actions, and hidden information, where the agent retains private knowledge inaccessible to the principal. The following paragraph explores these concepts in detail and their implications for the investment process.

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Hidden information, known as adverse selection (Akerlof, 1970; Ross, 1973), occurs when one party in a transaction has superior knowledge about a product or service. This information asymmetry can cause inefficient markets or even market failure. The fundamental issue involves the information asymmetry present in the relationship between buyers and sellers. Typically, the seller possesses significantly more knowledge about the product - particularly regarding its quality - than the buyer. As a result, buyers may have difficulty accurately assessing product quality and must often depend on market statistics or average quality evaluations (Akerlof, 1970; Ross, 1973). The phenomenon known as the "Lemons Principle" (Akerlof, 1970) highlights a significant market challenge: when buyers can only assess products based on average quality, sellers of high-quality goods are often unable to obtain fair compensation for their superior offerings. Conversely, sellers with lower-quality products can benefit by selling at the same depressed average price. This dynamic may result in a decline in overall product quality and a contraction of the market or, in extreme cases, even its complete disappearance (Akerlof, 1970). To mitigate the effects of hidden information and adverse selection, possible solutions include using guarantees and warranties to declare product quality, which shifts the risk from the buyer to the seller and assures an expected level of quality. Additionally, professional licensing for doctors and lawyers or educational certifications indicates a certain degree of proficiency (Akerlof, 1970).

In addition to hidden information, another type of information asymmetry is hidden action, also referred to as moral hazard, which describes scenarios in which a principal cannot observe the actions of an authorized agent (Holmstrom, 1979; Jensen & Meckling, 1976). In this scenario, the principal does not have full knowledge of whether the agent is performing the intended actions. This asymmetry creates opportunities for agents to pursue personal interests or reduce effort levels without immediate detection by principals. As a result, Pareto-optimal risk sharing cannot be achieved, and instead, a second-best outcome is reached that balances the benefits of risk sharing with providing appropriate incentives (Holmstrom, 1979).

To address this issue, several opportunities exist, such as monitoring the agent during specific actions. However, comprehensive monitoring is often difficult or prohibitively expensive. Another approach involves leveraging additional information; even imperfect data regarding the agent's actions or the state of nature can generally enhance contract effectiveness. Such information enables a more precise assessment of the agent's performance, maintaining incentive structures for effort while reducing the loss of risk-sharing benefits. A signal is considered valuable if it offers conclusions about the agent's actions beyond what is inferred from outcomes alone (Holmstrom, 1979; Spence, 1973).

In the context of this research an agent can be defined as a company that issues a particular stock. This agent possesses superior information about the company's true value (V_F) compared to investors (the principal) ($V_I = E[\, V_F \mid S\,]$), as described in Section 0. Asymmetries such as hidden information (e.g., market potentials) and hidden action (e.g., unobservable actions) increase mispricing risks. PAT emphasizes monitoring, e.g., through annual financial statements, certifications, e.g., through audit reports, or signals through sentiments, and though manipulation risks persist.

In the following section, the central concepts of signaling theory will be defined.

2.1.2 Credible Information Transmission through Market Signals

The Signaling Theory is closely related to the broader discussion of information asymmetry in economic relationships (Akerlof, 1970). Such asymmetries can be mitigated through signaling, where observable characteristics are intentionally introduced into the market to convey hidden attributes (Akerlof, 1970; Spence, 1974). A signal is an observable characteristic that is conveyed by a party who has the ability to control and introduce it into the market. The acquisition of such a signal involves a cost, and it has the property of directly influencing its value when presented to another party (Spence, 1973).

The signaling effect was initially studied in the job market, where information is implicitly defined and communicated, such as during recruitment processes. In this context, signaling refers to employers requesting and individuals providing information about potential employees, which can influence hiring decisions, offered wages, and job assignments. This mechanism is relevant because employers are unable to directly observe an individual's productive abilities before hiring and making recruitment decisions, which are a form of investment with inherent uncertainty. Within this framework, personal attributes may be categorized as either signals or indices. Signals are observable characteristics associated with an individual that can be intentionally modified, whereas indices are also observable but reflect inherent traits that cannot be altered. These signals can influence processes such as recruitment, depending on the costs associated with the signal. The cost of signaling is important for distinguishing between applicants. A signal's effectiveness as a differentiator hinges on its costs having a negative correlation with productive capability. These costs may include

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direct financial expenditures, psychological costs, and time if productivity does not negatively correlate with signaling costs, individuals would invest in the signal similarly, rendering it ineffective for differentiation (Spence, 1973).

Within financial markets, Signaling Theory describes how corporations address information asymmetries. Since investors cannot directly evaluate a company's intrinsic characteristics, projected performance, or management abilities, firms use signaling mechanisms, which may involve costs, to convey information about their value. Dividend payments, share buybacks, or certifications such as audited financial statements serve as credible signals that only financially robust companies can sustain over the long term. Signaling costs correlate negatively with company quality - weaker companies cannot replicate them credibly. As a result, effective signals differentiate high-quality companies from low-quality ones, reduce investor uncertainty, and enable more informed investment decisions and more appropriate stock valuations even if mispricing based on manipulations like cosmetic accounting can be caused (Healy & Wahlen, 1999).

Following the discussion of fundamental theories, the next section examines the effects of cognitive distortions on investors' interpretation of signals and the resulting impact on information asymmetries. This forms the basis for understanding the role of information asymmetries in investment decisions.

2.2 Cognitive Biases and Signal Misinterpretation in Financial Markets

This section analyzes how cognitive distortions among investors result in biased interpretations of market signals and promote information asymmetries. Behavioral finance, also known as behavioral economics, examines the psychological biases that can impact investors' understanding of market indicators (Redawati & Rizani, 2023; Tversky & Kahneman, 1974). This theory asserts that heuristics and cognitive biases frequently influence investment decisions more than strictly rational processes. To clarify how these psychological biases may distort investors' interpretations of signals related to stocks, this section will briefly outline the key characteristics of heuristics and biases, especially in decision-making under uncertainty.

Heuristics are mental or general principles designed to simplify the process of evaluating probabilities or estimators. They make the complex task of calculating probabilities more manageable by reducing it to simpler assessment operations. These principles enable individuals to make rapid decisions by relying on intuition, instead of engaging in extensive cognitive processing. This approach can be contrasted with decisions that incorporate objective perspectives (Tversky & Kahneman, 1974).

Biases, unlike heuristics, refer to consistent and foreseeable errors in judgment arising from the use of heuristic approaches. Although heuristics can offer advantages, they occasionally lead to notable systematic inaccuracies. These errors do not solely depend on motivational factors and can occur even when individuals are rewarded for correct answers. In summary, biases are a direct consequence of heuristic processes. While heuristics tend to be efficient, their underlying simplifications may produce systematic and enduring errors, commonly identified as biases (Tversky & Kahneman, 1974).

To apply these concepts to the financial markets, key heuristics and biases will be briefly outlined. One such heuristic is the representativeness heuristic (Bondt & Thaler, 1985), which refers to investors' tendency to base decisions on recent information immediately upon receiving it rather than relying on statistically sound conclusions. In essence, the representativeness heuristic constitutes a cognitive bias whereby individuals depend on stereotypes or the most current information, often resulting in forecasts that lack a solid statistical foundation and are characterized by overreactions to new or dramatic events, while overlooking important baseline data (Bondt & Thaler, 1985). In the stock market, investors often categories certain equities as "growth stocks" based on recent performance, potentially disregarding the limited likelihood that companies can sustain elevated growth over an extended period. This inclination to perceive patterns within random sequences illustrates a key aspect of heuristic-driven decision-making (Barberis et al., 1998).

The second relevant heuristic is the availability heuristic (Barber & Odean, 2008). This refers to how individuals rely on accessible news or information about a topic when making judgments. The availability heuristic indicates that information that is quickly recalled is often regarded as more common, likely, or significant. The ease of retrieving information from memory can affect decisions and judgments. Notable events - such as news coverage, unusual trading volumes, or extreme returns - can impact individual investors’ buying behavior, reflecting the core mechanisms of this cognitive bias. Research suggests individual investors may be inclined to purchase stocks that first attract their attention, highlighting the influence of readily available or prominent information on decision-making (Barber & Odean, 2008).

These two heuristics can lead to certain systematic biases including, e.g., overconfidence bias or anchoring. The overconfidence bias leads traders to overvalue their information, often resulting in excessive trading. This frequent trading typically yields lower-than-expected returns that may not cover trading costs (Daniel et al., 1998; Odean, 1999).

Anchoring refers to the cognitive bias whereby individuals make insufficient adjustments when estimating numerical values from an arbitrary starting point. In financial analysis, this bias often results in analysts setting their earnings estimates - such as forecasted earnings per share - relative to the average within their specific sector. This sector average effectively serves as an anchor during the estimation process (Cen et al., 2013).

Both biases indicate that signals may mislead investors due to heuristic-driven judgments differing from rational analysis. This suggests that there must be an objective interpretation of stock market signals, free from heuristic bias.

The loss aversion described in prospect theory reinforces these heuristic-driven misinterpretations: when information is incomplete ($I_I \subset I_F$), investors tend to overestimate negative signals (S), which further exacerbates information asymmetries. For example, negative news reports may be interpreted as signs of a permanent loss in value, even though the fundamental value (V_F) remains stable (Kahneman & Tversky, 1979). The behavioral tendencies outlined above demonstrate the necessity of structured systems that can compensate for information asymmetry and heuristic-driven biases. DSS provide such a framework.

2.3 Decision Support Systems (DSS) - Theory to AI-DSS

This section presents DSS as a framework intended to address information asymmetry and support decision-making processes (Simon, 1960). These frameworks are related to communication theory, which describes how information flows are processed and analyzed. When one party - such as the sender - possesses a message with high entropy, resulting in considerable uncertainty for the receiver, and the channel capacity is constrained or subject to noise, the receiver inevitably acquires less information or faces increased uncertainty regarding the original message (Shannon, 1948).

When one party leverages this discrepancy in knowledge, it can result in information asymmetry. For instance, a sender who can encode messages more efficiently due to superior understanding of the statistical characteristics of the message or channel properties gains an informational advantage over a receiver lacking this insight or the capability to decode optimally (Shannon, 1948). The economic dimension of such asymmetries has also been widely discussed, highlighting the consequences of quality uncertainty and agency-related conflicts (Akerlof, 1970; Jensen & Meckling, 1976).

Essentially, DSS is characterized by the focus on supporting complex, non-routine management decisions through modeling and an iterative problem-solving process that incorporates human judgment, distinguishing them from systems that merely automate routine tasks or provide aggregated data (Gorry & Morton, 1971). Conceptually, a DSS can resolve the problem of information asymmetries based on the previous theory.

These tools are designed to assist decision-making processes (Khodashahri & Sarabi, 2013). Traditional DSS, in use since the popularization of spreadsheets in the 1980s, rely primarily on static models and predefined rules for data analysis (Mohamed, 2025; Poszler & Lange, 2024; Power, 2008; Zhengmeng & Haoxiang, 2011). These systems, which are often spreadsheet-based, offer a simple approach to financial modeling, budgeting, and basic predictive analytics (Mohamed, 2025; Power, 2008). However, they have limited ability to process large, heterogeneous data streams, and they do not adapt to the dynamic conditions of modern industrial or business environments (Poszler & Lange, 2024). Furthermore, complex scenarios can lead to inaccuracies due to their reliance on static snapshots of data and their susceptibility to human error (Mohamed, 2025).

In contrast, AI-powered DSS represent a significant advancement, leveraging modern technologies such as machine learning, deep learning, and natural language processing to analyze vast amounts of data from diverse sources, including the Internet of Things (IoT) and business systems (Poszler & Lange, 2024). Unlike the traditional systems without AI, AI-powered systems can process information in real time, recognize complex patterns, and generate predictive insights that go beyond simple reactive analysis (Mohamed, 2025). These systems automate cumbersome tasks, continuously learn from new data to refine their recommendations, and can adapt to changing conditions, improving operational efficiency, reducing costs, and increasing decision accuracy (Dutta et al., 1994; Mohamed, 2025; Poszler & Lange, 2024). This adaptability makes them particularly valuable in dynamic environments where rapid, data-driven decisions are essential (Mohamed, 2025).

In financial market practice, AI-powered DSS analyze alternative data points and behavior in real time to improve credit decisions and identify financial risks (Bartelt & Röser, 2024a, 2024b; Cao, 2021; Pahsa, 2024). Giving a practical example, AI-powered chatbots such as

"Arturito" in Peru provide personalized customer service for tasks such as currency conversions and credit card payments, thereby reducing operating costs for banks (Pahsa, 2024). Another application is personalized banking and robot-based advisors, which use AI to assess consumer behavior and offer automated investment advice, thereby increasing financial inclusion (Singh & Kaur, 2017). In addition, these systems are used for complex operational problems, such as developing sophisticated financial instruments like contracts for transferring weather risk that use AI to process satellite and agricultural data and enable automatic insurance payouts via smart contracts (Pahsa, 2024).

The integration of AI into financial DSS enables faster and more cost-effective delivery of financial products and services. These technologies are transforming high-end finance by improving decision-making processes across the entire service value chain, from credit decisions to commercial risk management (Pahsa, 2024).

After discussing DSS usage, the next section will outline AI applications in finance, highlighting ways to improve AI-DSS quality.

2.4 AI Applications in the financial landscape

This section will review recent advancements in AI applications within the finance sector. Accordingly, historical developments will be briefly discussed first. Current research and progress will be organized by topic, specifically addressing the research question.

AI applications have been used in finance for over 35 years (Dutta & Shekhar, 1988; Kimoto et al., 1990; Lapedes & Farber, 1987; Schöneburg, 1990). For example, a modular neural network (NN) was developed to predict the optimal timing of stock trades within the Japanese stock market. This study examines a forecasting system designed to offer guidance on the optimal timing for stock transactions. The system demonstrated strong performance during simulation exercises. An analysis of its internal representations enabled the extraction of rules governing stock price fluctuations through cluster analysis. Results indicate that the forecasting system achieved a higher correlation coefficient (0.527) on training data compared to individual NNs (ranging from 0.414 to 0.458). Furthermore, the NN outperformed multiple regression analysis, yielding a substantially higher correlation coefficient of 0.991 versus 0.543 (Kimoto et al., 1990). This finding has also been demonstrated by several studies, which highlight the significant impact of AI adoption in the financial sector (Chintalapati & Pandey, 2022; Dutta & Shekhar, 1988; Schöneburg, 1990).

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Highlighting the relevance of NN in finance, a study analyzes the impact of NN in this research field and describes NNs as an advanced computer technology with broad application potential in finance (Burrell & Folarin, 1997). In many financial applications, these NNs outperform linear statistical and econometric models and offer advantages in modeling tasks with limited prior knowledge. The technology demonstrated significant potential in domains including credit scoring, portfolio management, financial forecasting, and risk analysis (Agal et al., 2025; Burrell & Folarin, 1997; Machado et al., 2025). Despite their successes, NNs have limitations, including the lack of a formal theory for optimal network topology, the computational intensity of training, and difficulties in interpreting results or debugging. Hybrid systems that combine NNs with expert systems or other techniques are proposed to overcome some limitations and improve overall performance (Burrell & Folarin, 1997). Further research is investigating broader applications, including the optimization of stock pricing using NNs. This study compares traditional Black-Scholes models with predictions generated by an NN. As well as in previous studies, the NN models achieved higher accuracy in price prediction (Anders et al., 1998).

Overall, these studies demonstrate the use of AI in the financial sector. The results obtained so far highlight the relevance of AI in traditional tasks such as price forecasting. Building on this, the following section focuses on current lines of research that address key topics such as risk and portfolio management. In addition, more advanced applications of AI will be examined to illustrate ongoing research and developments related to its use in finance. Recent publications indicate that AI now impacts almost every part of the banking value chain - including payments, banking, capital markets, investment management, and insurance - through applications such as machine learning algorithms, chatbots, and complex legal or compliance workflows (Ali et al., 2025; Fernandez, 2019; Valencia-Arias et al., 2025).

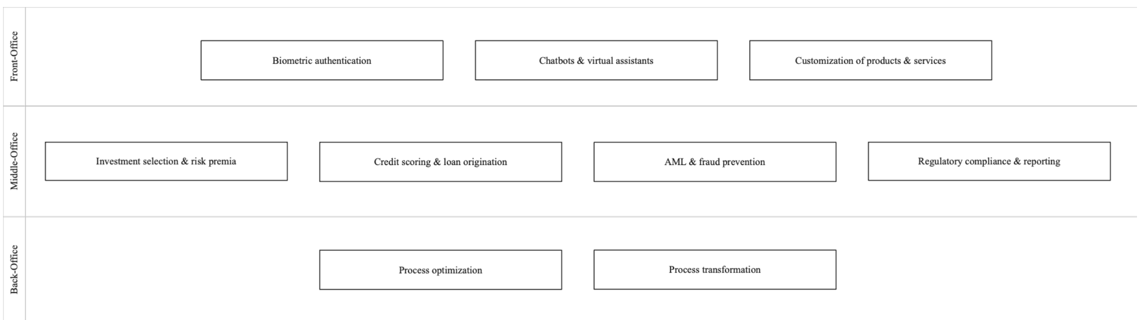

Figure 2: Applications of AI within the value chain of financial institutions

Source: own elaboration

Therefore, the discussion of AI applications in finance will be organized by topics according to areas of research relevance. The primary topics related to the research are risk management and portfolio and asset management. The next section outlines the practical application of AI in risk management.

AI in risk management procedures

The integration of AI into risk management has become increasingly relevant, especially as regulatory standards such as the Basel Framework evolve to require improved accuracy and transparency in credit risk assessment (Heß & Damásio, 2025). Traditional approaches have primarily depended on static financial ratios and historical default data, which often do not consider alternative and unstructured information. AI addresses this limitation by facilitating the integration of diverse and large-scale data sources. AI enables the use of diverse, large-scale data sources, resulting in the creation of dynamic and more accurate risk profiles (Lui & Lamb, 2018). AI and ML are revolutionizing financial risk management through improved data analysis, pattern recognition, and prediction. These technologies advance conventional risk management methodologies in areas such as credit, market, and operational risk by efficiently processing extensive and varied datasets to deliver actionable insights and automate sophisticated decision-making processes (Aziz & Dowling, 2019). Among the different risk categories, credit risk management stands out as a field where AI has had a particularly strong impact (Heß & Damásio, 2025). AI has significantly improved credit risk management, which involves assessing the likelihood of a borrower defaulting on their obligations (Bussmann et al., 2021). AI models can analyze a much wider range of data than traditional credit scoring systems (Bussmann et al., 2021; Sadok et al., 2022). This allows increased objectivity and reliability in financial intermediation for the identification of subtle indicators of creditworthiness and supports (Lui & Lamb, 2018; Sadok et al., 2022).

A potential benefit of AI is that it may lower bias in credit decisions. Studies indicate that financial institutions using AI for mortgage approvals can reduce discrimination rates by up to 40% compared to traditional methods (Bartlett et al., 2022; Sadok et al., 2022). Beyond that, the use of big data extends the range of information sources far beyond traditional financial datasets. Big data refers to the massive, fast-moving, and diverse sets of information that require advanced analytical techniques to extract value (Laney, 2001). By leveraging big data - incorporating not only conventional datasets but also sources such as social media, online behavior and digital fingerprints - it is possible to conduct more accurate creditworthiness assessments, thereby enabling improved predictions of default probability levels

(Berg et al., 2020; Sadok et al., 2022). The utilization of enriched datasets enables institutions to conduct more thorough background checks, including on companies with limited credit histories. This approach allows institutions to approve credit requests for firms lacking extensive credit records by relying on the available data (Sadok et al., 2022). Beyond these improvements in credit assessment, AI also contributes to gains in efficiency and productivity. Additionally, AI can improve productivity in data modeling and decision-making processes (Agrawal et al., 2019; Bartelt & Röser, 2024b, 2024a).

Overall, these findings indicate that AI improves several components of financial risk management. Implementing AI in certain areas has the potential to increase banking process efficiency by up to 20% (Fuster et al., 2019). As a result, credit analysis and risk management practices within financial institutions may undergo significant changes (Sadok et al., 2022). The following paragraph briefly examines AI applications in portfolio and asset management.

AI in portfolio- and asset management

In addition to risk management, the advantages of AI can be leveraged in portfolio and asset management by improving decision-making, optimizing trading activities, and managing risks more effectively (Cao, 2021; Chirumamilla & Manikandan, 2024; Hayat & Shoeb, 2024). These advanced technologies enable the comprehensive analysis of large datasets, identification of market trends, and automation of intricate financial processes, thereby outperforming traditional approaches and supporting more sophisticated, data-driven investment strategies (Pahsa, 2024; Pawar et al., 2024).

Asset management uses AI in areas like algorithmic trading and credit underwriting. These technologies increase transaction execution speed and efficiency and enable portfolio strategies that use real-time data and advanced modeling. Another application of AI in emerging market financial services is automating processes to lower transaction costs for a wider range of customers. The adoption of AI-driven systems enables financial institutions to automate complex tasks such as trade execution, risk assessment, and asset allocation, thereby reducing human error and responding dynamically to market fluctuations. Furthermore, AI models facilitate more profound analysis of large and diverse datasets, improving the accuracy of forecasting and supporting more informed investment decisions (Bartelt & Röser, 2024a; Cao, 2021; Pahsa, 2024).

In asset management, risk management models play an important role. Machine learning is particularly useful for testing the resilience of market models to identify potential risks in trading behavior. To provide a practical example, the French investment firm Natixis conducts millions of simulations each night using unsupervised learning to detect patterns and connections between assets (Woodall, 2017). Major trading firms are utilizing AI, particularly clustering techniques, to optimize their operations. These approaches help mitigate the substantial costs associated with executing large trades in illiquid markets (Aziz & Dowling, 2019; Golić, 2020; Koshiyama et al., 2020). AI and machine learning also facilitate the discovery of subtle relationships between assets, enabling firms to establish strategic positions by transacting through a series of interconnected assets rather than relying on a single significant trade (Aziz & Dowling, 2019).

In summary, AI technologies serve as an essential tool in transforming the financial industry and advancing its development. AI enables substantial data enrichment and model optimization in finance, according to analyzed studies. These findings demonstrate that integrating underlying theories, DSS frameworks and AI technologies can be an effective strategy for addressing information asymmetry in individual stock investment decisions.

2.5 Integration and Implications for the Research Project

The previous sections have provided the necessary theoretical background to understand information asymmetries in financial markets, their impact on investment decisions, and how AI-DSS could address these challenges. This chapter integrates the PAT, Signaling Theory, behavioral finance, and DSS to derive implications for the research project, which aims to investigate how AI-DSS can reduce information asymmetries and enhance stock valuation accuracy.

Information asymmetries, formally defined as $\Delta I = I_F \setminus I_I$, where I_F represents the company's information set and $I_I \subset I_F$ the investor's, are central to the research problem. PAT elucidates how hidden information (adverse selection) and hidden action (moral hazard) create conflicts of interest, leading to potential mispricing ($V_I \neq V_F$) (Akerlof, 1970; Jensen & Meckling, 1976). The Signaling Theory explains that companies use certain costly signals (S), such as audited financial statements or dividend payments, as a means to convey information about their value to investors V_F. These signals incur cost $C(S)$, which are negatively correlated with company quality, ensuring that only high-quality firms can sustain them (Leland & Pyle, 1977; Spence, 1973). In contrast, signals that can be manipulated at low cost - such as cosmetic accounting - do not meet this credibility requirement and may instead amplify mispricing risks (Healy & Wahlen, 1999). Behavioral finance also reveals how cognitive biases distort investors' understanding of signals. Formally, the perceived signal by investors can be modeled as $S_I = f(S, B)$, where B represents cognitive biases such as representativeness, availability, overconfidence, or loss aversion, leading to irrational decisions and increased market volatility (Barberis et al., 1998; Kahneman & Tversky, 1979; Pursiainen, 2022).

Traditional DSS frameworks facilitate decision-making by consolidating data and utilizing fixed models (Gorry & Morton, 1971). However, their limitations in handling dynamic, heterogeneous data streams restrict their effectiveness in modern financial markets (Mohamed, 2025). AI-DSS, as a specific implementation of a method $M \in \mathcal{M}$, overcomes these limitations by leveraging machine learning, natural language processing, and real-time data analysis to process diverse data sources (e.g., financial reports, market trends, social media). These systems minimize the expected deviation between perceived and true stock value $E[| V_F - V_I |]$ by aggregating signals, correcting biases in S_I, and personalizing risk profiles (Koshiyama et al., 2020; Shah, 2014). For example, AI-driven sentiment analysis mitigates overreactions to negative news, while advanced risk models enhance creditworthiness assessments and reduce discrimination in financial decisions (Bartlett et al., 2022).

For the research question, these theoretical frameworks underpin a hypothesis: AI-DSS, as a method $M \in \mathcal{M}$, can reduce information asymmetries (ΔI) by aggregating multi-source data, correcting heuristic-driven distortions in S_I, and tailoring investment recommendations to individual risk preferences. The thesis will empirically test this hypothesis using a DSR approach, developing an AI-DSS that processes signals (S) - such as financial statements, market sentiments, and alternative data - and evaluates their impact on stock valuation accuracy. The system will incorporate technologies like machine learning and web scraping to generate tailored investment reports, addressing ethical considerations such as transparency and bias mitigation (Kruse et al., 2019). The findings are expected to contribute to the literature by bridging theoretical models and practical applications, enabling more informed, equitable, and efficient investment decisions in financial markets.

The following chapter outlines the methodology for the thesis and is structured according to established DSR principles (Hevner et al., 2004; Peffers et al., 2007; Vom Brocke & Maedche, 2019).

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3 DESIGN AND DEVELOPMENT OF THE AI-DSS

The research design of this project applies the DSR approach (Hevner et al., 2004; Peffers et al., 2007). This chapter presents the design, guided by the idealized blueprint of DSR, and thus an overview of the methodological approach in developing an AI-DSS. The next section will describe the research design in detail. Subsequently, the architecture of the artifact and its components will be outlined, demonstrating how the artifact functions and identifying its key components. Finally, the data collection, preparation and operationalization processes will be described.

3.1 Research Design

The research design is conceived as a theory-driven, deductive, non-experimental empirical field study that collects longitudinal data at multiple points in time (Dinh et al., 2022; Döring, 2023; Pfaffenberger, 2016) . It is based on PAT (Jensen & Meckling, 1976; Ross, 1973), which defines the problem of information asymmetries and uses primarily collected data, with secondary analyses possible in an open science context. The design process may be segmented into the following functional phases, which encapsulate the stages of the DSR methodology:

1. **Design and development phase**: Development of an AI-DSS in a single build phase, based on established quantitative methods (e.g. ARIMA, GARCH, NLP) and objectives formulated with the feedback of industry leaders (Hevner et al., 2004).
2. **Evaluation phase**: Two-part evaluation through framework analysis (research question) and quantitative questionnaire (hypothesis), focused on Eval 3 (solution instantiation) and Eval 4 (solution in use) of the DSR approach *(Sonnenberg & Vom Brocke, 2012)*.

The evaluation dispenses with Eval 1 (problem identification) and Eval 2 (solution design), which is methodologically justified:

- Eval 1: The PAT defines the problem of information asymmetries clearly and soundly *(Eisenhardt, 1989; Jensen & Meckling, 1976; Ross, 1973; Shah, 2014)*. Additional validation of the problem identification (significance, novelty, feasibility) is therefore not necessary. The relevance arises from the practical importance of inefficient capital allocations, and the feasibility from available technologies such as AI and web scraping *(Sonnenberg & Vom Brocke, 2012)*.

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- Eval 2: The design of the AI-DSS is based on established and validated methods (e.g. ARIMA, GARCH, NLP)*(Araci, 2019; Box, 2013; Liu, 2020)* and a four-layer architecture (λ-Knowledge). A separate design evaluation is therefore not necessary*(Sonnenberg & Vom Brocke, 2012)*.

The research design is based on the quality criteria of the DSR methodology (relevance, rigor, transparency, validity, reliability), discussed and evaluated during the evaluation phase *(Peffers et al., 2007)*.

For a transparent presentation of the research project, the representation as a DSR grid is used; see Table 1. This format has proven itself in scientific literature on design search research and follows the current state of research (Vom Brocke & Maedche, 2019).

Table 1: DSR-Grid: Overview of the research project

Element	Description
Problem Description (J. R. Venable et al., 2019)	Information asymmetries between investors and companies in the financial market, clearly defined by the PAT, make well-founded investment decisions difficult and lead to inefficient capital allocations.
Input Knowledge (Gregor & Hevner, 2013)	Ω-Knowledge: Principal-agent theory, literature on information asymmetries(Eisenhardt, 1989; Shah, 2014) . λ-Knowledge: Existing AI and data science models and web scraping technologies(Araci, 2019; Bartelt & Röser, 2024a; Cao, 2021; Yang et al., 2023)
Research Process (Hevner et al., 2004)	Development of an AI-DSS in a single build phase with time series analysis, risk management and sentiment analysis, followed by an evaluation through framework analysis (research question) and quantitative questionnaire (hypothesis).
Key Concepts (Vom Brocke & Maedche, 2019)	Information asymmetries, risk willingness, AI-DSS, time series analysis, sentiment analysis, risk management, framework analysis, expert validation.
Solution Description (J. R. Venable et al., 2019)	An AI-DSS with four layers (input, data analysis, scoring, output) that generates customized reports comparable to established investment reports.
Output Knowledge (Gregor & Hevner, 2013)	Design knowledge (λ-knowledge) about the design of AI reports to reduce information asymmetries, validated by comparison with investment reports and expert feedback.

Source: own elaboration

The two phases outlined above collectively encompass all six phases of the DSR methodology (Peffers et al., 2007), see Figure 1. The design and development phase integrates the initial problem identification, objective definition, and artifact design and development stages, while the evaluation phase covers demonstration, evaluation, and communication activities. This structured approach extends the standard DSR process by strategically omitting Eval 1 (problem identification) and Eval 2 (solution design), as these are adequately covered by the principal-agent theory foundation and established methodological approaches. This ensures high methodological quality with a focused, single-iteration process that systematically addresses the defined research question.

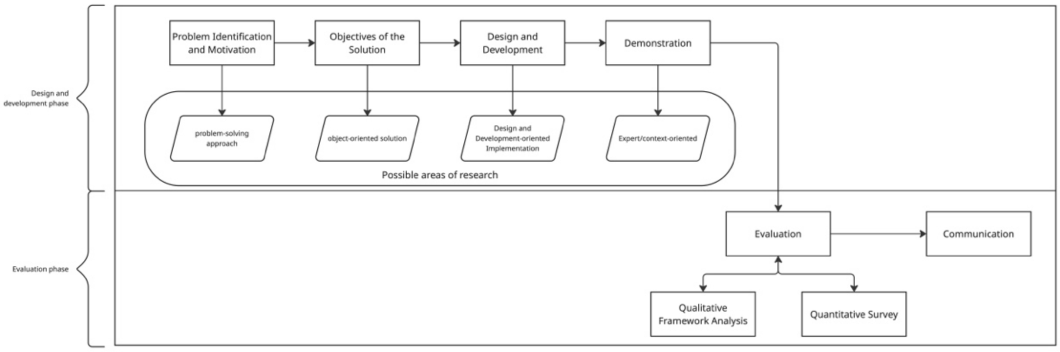

Figure 1: Illustration of the DSR process

Source: own elaboration, Adapted from Peffers et al. 2007

3.2 Architecture and Components

This section describes the architecture and components of the AI-DSS. The clear problem definition provided by PAT enables direct artifact development in a single build phase without iterative exploration. The AI-DSS consists of four coordinated layers that build on each other in terms of process; see Figure 3.

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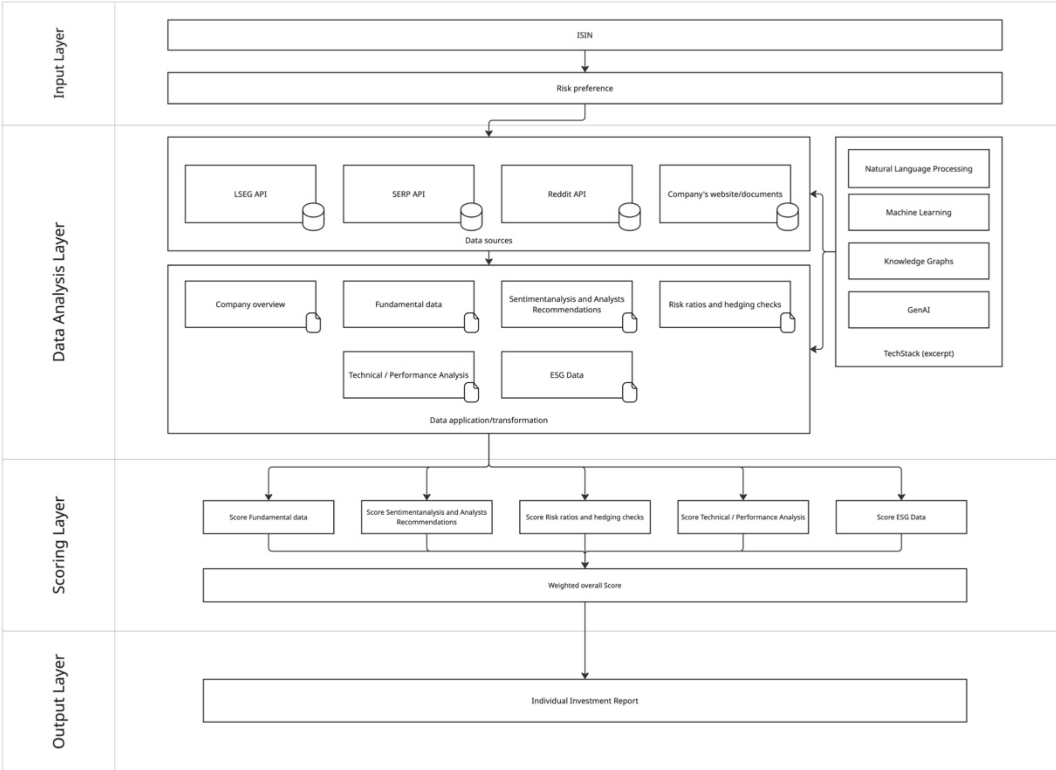

Figure 3: Development design of the AI-DSS

Source: own elaboration

The following sections will explain the model's functionality and how the goals in the introduction will be met for the artifact.

3.2.1 Input Layer

In the input layer, users are required to input the ISIN and specify their risk preference (Figure 4). The determination of the risk preference will be based on quantitative structured questionnaires in accordance with the relevant regulatory guidelines, like MiFID II (European Union, 2014; Gortsos, 2018; Kümmerle & Conen, 2018). To comply with regulations, the AI-DSS adheres to strict rules for retail investors. This method can be used to satisfy strict regulatory rules. While other investor groups, like professional clients and eligible counterparties, don't have to answer all the detailed questions for investing, it's still a helpful way to cover all situations in AI-DSS development.

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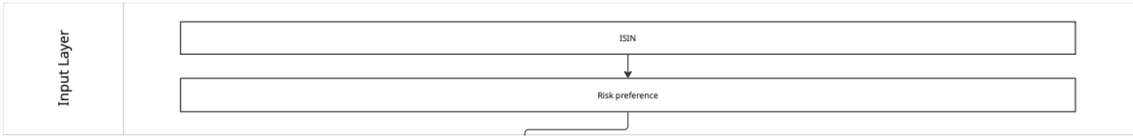

Figure 4: Input Layer

Source: own elaboration

The overall risk preference is determined by two dimensions evaluating both risk tolerance R_t and risk willingness R_w. Each dimension will be assessed through five indicator questions. These questions can be answered using an indicator value $s_i \in \{1, 3, 5\}$, where each response s_i represents the individual's stance on the respective question. Where $s_i = 1$ indicates a low risk, $s_i = 3$ indicates a moderate risk and $s_i = 5$ indicates a high risk. The questions about the R_t cover investment horizon, debt level, asset value, income securities and investment objectives. The questions about the R_w focus on psychological risk tolerance, like preferences for yield versus security. The indicators match established risk profiles and comply with national regulations that determine exact formulations (Gortsos, 2018; Grable & Lytton, 1999).

Each dimension can be scored using the formula: $S_d = \sum_{i=1}^{n} s_i$, $d \in \{t, w\}$ where S_d represents the score for the dimension d (R_t *or* R_w) and s_i denotes the individual's stance on the respective question (n=5). Given the discrete response options $s_i \in \{1, 3, 5\}$, the score s_d lies in the discrete range $\{5, 7, 9, \ldots, 25\}$, with a minimum score of $S_d^{min} = 5$ (all answers equal 1) and the maximum score being $S_d^{max} = 25$ (all answers equal 5). The results section consolidates responses and determines the risk profile. It displays the scores for both dimensions, their respective categories (risk-averse, risk-neutral, risk-affine) and the overall risk profile, which is determined conservatively. This classification can be formulated as a discrete classification function

$$C(S_d) = \begin{cases} risk\ averse, if\ 5 \leq S_d \leq \tau_1, \\ risk\ neutral, if\ \tau_1 < S_d \leq \tau_2, \\ risk\ seeking, if\ \tau_2 < S_d \leq 25, \end{cases}$$

where the thresholds $\tau_1 = 12$ and $\tau_2 = 18$ are preset based on preliminary assumptions to promote a conservative yet balanced classification, pending further validation. These thresholds aim to align with MiFID II's investor protection requirements by ensuring that the risk-averse category is sufficiently broad to capture cautious investors, while allowing differentiation across risk profiles (European Union, 2014; Gortsos, 2018).

The overall risk preference P is determined conservatively by selecting the lower category of the two dimensions: $P = \min\big(C(S_t), C(S_w)\big)$, where the categories follow an ordered hierarchy: $risk\ averse\ \prec risk\ neutral\ \prec risk\ seeking$. This conservative approach prioritizes the lowest risk to align with the investor's risk profile, ensuring protection against potential losses, especially for those with low risk tolerance. By focusing on minimizing risk, the system adheres to MiFID II regulatory requirements, which mandate that recommendations serve the client's best interest and match their risk preferences. This risk-averse strategy also enhances the system's modular and scalable design, facilitating compliance and adaptability across diverse investor profiles. This conservative aggregation logic ensures that if either dimension indicates a lower risk willingness , the overall profile reflects this caution, aligning with MiFID II's mandate to prevent excessive risk exposure for retail investors (Europäisches Parlament und Rat der Europäischen Union, 2014). This design choice prioritizes investor protection by reducing the likelihood of assigning a risk profile that exceeds the investor's financial capacity or psychological willingness to bear risks.

The combination of these two variables (risk tolerance and willingness) is essential for generating the investment report and establishing the foundation for the Data Analysis Layer. The results consolidate the scores S_t and S_w, their respective categories $C(S_t)$ and $C(S_w)$ and the overall risk preference P. These are presented in a structured format, serving as input for a downstream analysis function $f(P, D)$, where D encapsulates additional investor attributes (e.g., ISIN).

3.2.2 Data Analysis Layer

The ISIN and risk preference from the input layer are stored as $f(P, D)$, forming the basis for data analysis conducted in the data analysis layer (Figure 5).

The input function can be declared as $f: P \times D \rightarrow \mathcal{I}$, where $P = \{risk\ averse, risk\ neutral, risk\ seeking\}, D = \{valid\ ISIN\}, \mathcal{I} = (P, ISIN)$. Based on the input $\mathcal{I}$, the data analysis core then retrieves data from various interfaces (APIs) described as $DS = \{DS_{LSEG}, DS_{SERP}, DS_{Reddit}, DS_{web}\}$, which are either license-free or subject to licensing. The necessity of utilizing a licensed data source for data retrieval (DS_{LSEG}) arises from the lack of free APIs capable of handling comprehensive datasets for every individual stock. Conducting such an analysis on a partial dataset is not feasible. Since DS_{LSEG} does not cover all perspectives for an investment report, other sources are integrated as well.

These heterogeneous data sources DS_i are relevant, to cover all relevant data for analyzing a single company, where

- DS_{LSEG}: $LSEG\ API$ is used as a reliable financial database providing financial data (e.g., prices, fundamentals, stock-related news),
- DS_{SERP}: $SERP\ API$ retrieves the latest annual reports via web searches for the company associated with ISIN,
- DS_{Reddit}: $Reddit\ API$ provides raw data (posts/comments) related to ISIN for sentiment analysis (Aroussi, 2019),
- DS_{web}: $Company\ websites\ provided\ by\ Serp\ API$ sources annual reports for the company linked to the ISIN (Freelon, 2018; Luscombe et al., 2022).

Scientific soundness of Reddit as a social-media source is addressed in Section 4.2.3. Search algorithms implemented via the SERP API (DS_{SERP}) expand the set of sources by using the function $DS' = \sigma_{search}(DS, ISIN)$, where σ_{search} is a search function identifying additional web sources relevant to the company associated with the Theses sources include, for example, company websites hosting annual reports or other financial documents. The expanded set $DS' \supseteq DS$ includes the original sources in DS and new sources $DS_{new} \in DS' \setminus DS$ such as specific web pages retrieved via SERP API searches, which are then accessed using their respective retrieval mechanisms.

For each source $DS_i \in DS'$ data is retrieved using $D_i = r_i\big(DS_{i,}P_i, ISIN\big)$, where P_i is the access parameter (e.g. API keys for LSEG, URLs for web) and r_i is the individual retrieval mechanism (e.g. r_{LSEG} queries LSEG API for financial data and news specific to ISIN). The retrieved datasets $\{D_i\}_{i\,\in\,DS'}$ from the output of the data retrieval are tailored to ISIN and supporting the heterogeneous data strategy.

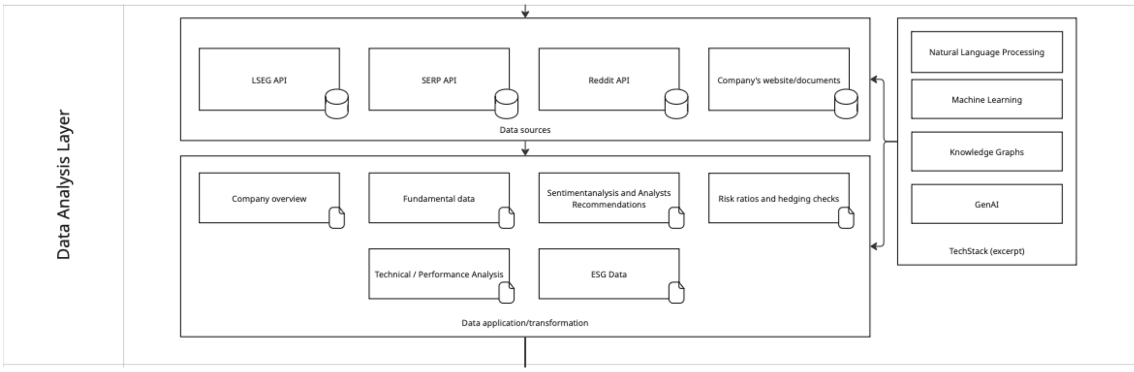

Figure 5: Data Analysis Layer

Source: own elaboration

After accessing the APIs, various data collection and preparation methods, along with algorithms, are employed to obtain company descriptions, fundamentals, sentiment analysis results, performance KPIs, ESG data and risk assessments. These methods are detailed in Section 4.1 for data collection and preparation and in Section 4.2 for conceptual operationalization and the integration of the tech stack.

3.2.3 Scoring Layer

The scoring layer utilizes the data obtained from the data analysis layer, as provided by various sources described in Section 3.2.2. It acts as an intermediary between data retrieval (data analysis layer) and investment report generation (output layer), calculating scores for each section based on criteria outlined in Section 4.1.1 (Figure 6).

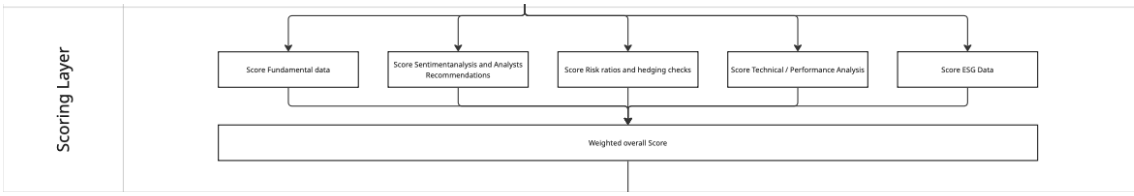

Figure 6: Scoring Layer

Source: own elaboration

These scores are relevant for checking, if an investment equals the individual risk preference, or not. Therefore, it does a data aggregation to consolidate the datasets given by the data analysis layer $\{D_i\}_{i \in DS'}$ into categorizes datasets D_k for the analysis categories

$k \in K$ with $K = \begin{Bmatrix} fundamental\ data, sentiment\ analysis, risk\ metrics, \\ hedging\ results, performance\ metrics\ and\ ESG\ data \end{Bmatrix}$. The aggregation is performed by a function $D_k = \alpha_k(\{D_i\}_{i \in DS'})$ where α_k represents the specific aggregation logic for category k. For example, fundamental data such as earnings or revenue are extracted from DS_{LSEG} and annual reports (DS_{SERP}, DS_{web}), while sentiment analysis processes text data from DS_{Reddit}. The detailed preprocessing steps (e.g., cleaning Reddit data, normalizing financial data) are described in Section 4.1.2.

For each analysis category $k \in K$ an individual score S_k is computed to quantify the company's performance in that category. The score is based on a set of category-specific criteria C_k and is calculated using a scoring function $S_k = \beta_k(D_k, C_k)$ where β_k represents the scoring logic. The individual scores S_k are normalized to the range $[0, 100]$ to enable consistent aggregation. This is necessary to ensure the comparability of heterogeneous categories and to avoid implicit distortions during aggregation. For instance, fundamental data may evaluate criteria such as earnings consistency over ten years while risk metrics may consider volatility or Value-at-Risk (Section 4.2.2).

These individual scores $\{S_k\}_{k \in K}$ are aggregated into a total score S_{total} that serves as the basis for comparing the investor's risk preference with the risk provided by the company. The aggregation is performed by a weighted sum: $S_{total} = \sum_{k \in K} w_k \times S_k$, where w_k are the weights for each category, satisfying $\sum_{k \in K} w_k = 1$. The weights account for the risk preference P from the input layer (Section 3.2.1) to ensure a conservative evaluation in accordance with MiFID II requirements. The specification of the criteria C_k, the scoring logic β_k and the weights w_k is detailed in Section 4.1.

3.2.4 Output Layer

The Output Layer integrates data from previous layers into the investment report. This final layer generates the completed investment report (Figure 7). The Layer integrates the investor's risk preference (P), heterogeneous datasets $\{D_i\}_{i \in DS'}$ and scores $\{S_k\}_{k \in K}$ alongside the total score S_{total} from the Scoring Layer to generate a structured investment report in PDF format, denoted as R_{PDF}.

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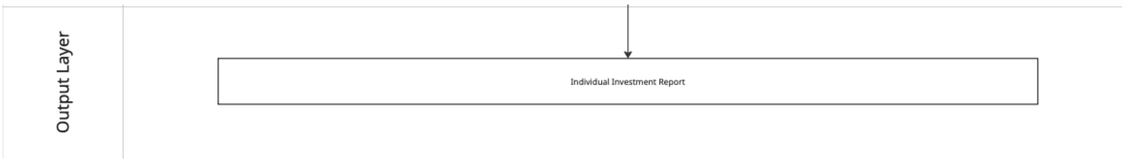

Figure 7: Output Layer

Source: own elaboration

The risk preference $P = \min\big(C(S_t), C(S_w)\big)$, where $C(\cdot)$ maps risk tolerance S_t and willingness S_w to categories $\{risk\ averse, risk\ neutral, risk\ seeking\}$, guides the conservative evaluation. A Multi-Agent System (MAS), comprising agents A_k for each category $k \in K = \begin{Bmatrix} fundamental\ data, sentiment\ analysis, risk\ metrics, \\ hedging\ results, performance\ metrics\ and\ ESG\ data \end{Bmatrix}$ processes the datasets D_k and scores S_k against criteria C_k yielding category-specific outputs $O_k = \gamma_k(D_k, S_k, C_k, P)$. These outputs, combined with P, S_{total} and the ISIN, are synthesized by a Large Language Model (LLM) via $R = LLM(\{O_k\}_{k \in K}, S_{total}, P, ISIN, \theta)$, where θ denotes the LLM configuration. The resulting report $R_{PDF} = \phi(R)$, formatted as a PDF, includes the investor profile, analysis results, total score and MiFID II-compliant recommendations, ensuring a conservative alignment with P. This process, formalized as $R_{PDF} = \phi \circ LLM \circ \gamma(\{D_i\}_{i \in DS'}, \{S_k\}_{k \in K}, S_{total}, P, ISIN, \{C_k\}_{k \in K}, \theta)$ ensures modular, scalable and regulatory-compliant decision support.

3.2.5 Interaction between the Layers

The AI-DSS has four connected layers - Input, Data Analysis, Scoring, and Output - that work together to turn user inputs into a customized investment report. These layers work one after the other, with each layer adding to the one before it to create a clear and efficient decision support tool that meets regulations and is tailored to the user.

Upon retrieving the relevant data, it is transferred to the scoring layer. This layer assesses whether the asset aligns with the preconfigured risk preference of the investor. The model then weights the analysis results to generate an overall rating score. The final layer, more precisely the output layer, produces a customized investment report based on the investor's risk willingness and specific individual stock, including relevant sections as well as the total score.

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The components of the AI-DSS utilize established methodologies grounded in current research incorporating ratio calculations, trend analyses, statistical models, and sentiment analyses (Araci, 2019; Bartelt & Röser, 2024a, 2024b; Box, 2013; Liu, 2020).

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4 DATA COLLECTION AND OPERATIONALIZATION

This chapter describes the data collection and operationalization processes. It is divided into two main sections. The first section details the methods used for data collection and preparation, while the second section explains the conceptual operationalization of three main components and their analytical implementation.

4.1 Data Collection and Preparation

This section details the methods used for data collection and preparation. Due to the restrictions of the given APIs and the principle of data economy, each data source's relevant history depth, window and fetch mode are described. This part establishes the foundation for the data preparation modes that are essential for the data analysis. Additionally, the interaction with the AI-DSS is explained.

4.1.1 Data Retrieval and Frequency

As in the architecture described, the AI-DSS takes use of multiple, heterogeneous data sources $DS = \{DS_{LSEG}, DS_{SERP}, DS_{Reddit}, DS_{web}\}$ to provide a multi-sided overview of the company underlying the given stock via ISIN and the individual risk preference. Across modalities, time horizons are calibrated to analytical objectives: long-run fundamentals address structural trends and valuation cycles, short-run discourse enables sentiment nowcasting, and medium-horizon market quotes support exposure and risk estimation under typical seasonality and monthly rebalancing conventions. The data is based on the provided ISIN and requires a license for use, accessible through API frameworks from the distributors of each data source. The retrieval process can be formalized as $D_i = r_i(DS_i, P_i, ISIN)$ and operates sequentially to optimize computational efficiency as well as API restrictions (see Section 3.2.2). Conceptually, the horizon P_i is selected to balance signal stability and timeliness for each modality, minimizing noise for slow-moving fundamentals while preserving responsiveness to fast-moving sentiment and market risks. Each source is configured with precise temporal parameters to align with its analytical objectives within a targeted sample. For instance, financial data from DS_{LSEG} spans up to a 10-year history to support long-term trend analysis. A ten-year span typically covers at least one full business and rate cycle, enhancing the robustness of trend, valuation, and factor estimates by capturing structural regime variation rather than transient shocks. Reddit data from DS_{Reddit} covers a 7-day period to capture recent market sentiment. A seven-day window balances recency with noise reduction, smoothing single-day spikes while remaining sensitive to event-driven sentiment dynamics typical for retail forums. Annual reports from DS_{SERP} provided via DS_{web} are retrieved for the past year, providing strategic insights. Restricting the scan to the most recent reporting cycle prioritizes the latest management disclosures (e.g., MD&A and risk factors), which are primary drivers of updated strategic and governance signals. Commodity/foreign exchange (FX) quotes from DS_{LSEG} are accessed over a 1-year period with a 21-day rolling window to analyze risk exposures. A one-year horizon captures seasonal patterns and medium-term co-movements, while a 21-day rolling window approximates a trading month and stabilizes beta and correlation estimates used in exposure and risk attribution. The sequential fetch mode ensures that data dependencies are preserved, with each source contributing specific variables, such as financial ratios, document links, token corpora, and price vectors, as summarized in Table 2.

Table 2: Temporal Setup and Variable Scope (Sequential Retrieval)

Feed (Execution Order)	History Depth	Window	Fetch Mode
LSEG Fundamentals & Prices	Up to 10 years	-	Single
SERP Annual-Report Scan	1 year	-	Single
Reddit Discourse	7 days	-	Single
Commodity/FX Quotes via LSEG	1 year	21 days	Single

Source: own elaboration

4.1.2 Data Preparation Methods

The raw datasets $\{D_i\}_{i \in DS'}$ are transformed into analysis-ready formats D_k for categories $k \in K = \begin{Bmatrix} fundamental\ data, sentiment\ analysis, risk\ metrics, \\ hedging\ results, performance\ metrics\ and\ ESG\ data \end{Bmatrix}$ using the preparation function $D_k = \alpha_k(\{D_i\}_{i \in DS'})$. DS' is the index set identifying heterogeneous data sources (e.g., LSEG, annual reports, Reddit data; see Section 3.2.2), and i iterates over these sources in $\{D_i\}_{i \in DS'}$. The preparation function α_k maps these datasets to category-specific formats D_k, where k indexes analysis categories (e.g., fundamental data, sentiment analysis; see Section 3.2.3). No condition $i < k$ is required, as i and k index distinct sets. This process ensures compatibility with the scoring layer's quantitative evaluations and the output layer's LLM-based contextualization. The following preparation pipeline follows three stages:

cleaning, normalization and structuring. For financial data from DS_{LSEG}, missing values in financial ratios are imputed using linear interpolation for time series data. The text data from $DS_{SERP}, DS_{Reddit}, DS_{web}$ undergoes tokenization, stop-word removal and lemmatization. Irrelevant content is filtered through keyword-based heuristics and duplicates are removed to produce a clean token corpus. In practice, relevance is enforced via inclusion and exclusion lexicons, where inclusion keywords cover annual reports across different languages and synonyms, combined with exclusion lists that filter out false positives such as corporate responsibility or sustainability reports. Additionally, domain- and path-based credibility checks are performed, including official domain detection through company name tokens, requirements for PDF extensions, and path scoring that considers the presence of company names and year indicators. Document structure cues such as annual report identifiers in filenames or paths, as well as regex-based patterns for fiscal years, are also utilized. Lightweight fuzzy matching identifies near-match mentions, applying a fuzzywuzzy partial_ratio of at least 85 for company name variants in Reddit titles, for instance. Deduplication occurs at both URL and content levels, using methods like URL candidate deduplication via dict.fromkeys, headline-based filtering for news articles, submission.id uniqueness for Reddit, and normalization of commodity and currency codes post-extraction. Results that fail issuer or instrument validations - such as missing company names, ISINs, ticker/RICs, or invalid ISO-3 currency codes according to forex_python - are discarded prior to embedding. Commodity and FX data are validated for consistency, excluding generic values like "not specified", "various", or "none", with missing values imputed through forward-fill methods. FX quotes are converted to the trading currency by triangulating through a reference currency when direct trading pairs are unavailable, ensuring consistent valuation across assets. Normalization scales financial ratios and log prices to a [0, 1] range using min-max techniques, while text data is transformed into numerical representations, such as FAISS vectors for annual reports or BERT embeddings for social media posts (Araci, 2019; Douze et al., 2024). Commodity and FX quotes are smoothed with 21-day rolling averages to highlight trends. Structuring organizes datasets into formats suitable for analysis: time-series matrices for fundamental data, categorical scores for sentiment analysis and statistical aggregates for risk metrics. Metadata, such as document links and ISIN mappings, are indexed to ensure traceability and MiFID II compliance.

4.1.3 Analytical Components

The AI-DSS allows one to perform multiple analyses based on the prepared data mentioned earlier. Figure 8 provides an overview of all analyses using this data.

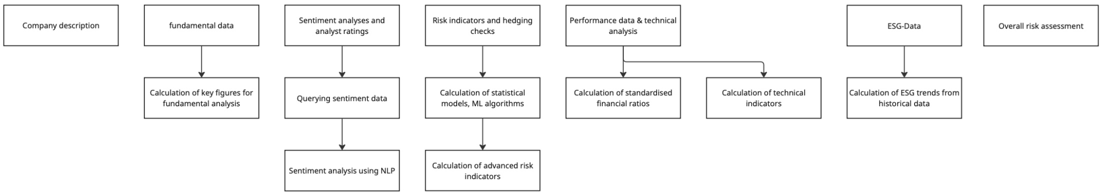

Figure 8: Analyses within the AI-DSS

Source: own elaboration

Based on the given dataset and the multi-sided analysis approach used in the AI-DSS development, the system makes use of both quantitative and qualitative methods to analyze the datasets, supporting the investment report objectives summarized in Table 3. The following details of each component focus on implementation specifics to complement the framework in Section 3.

Table 3: Selection of statistical components within the AI-DSS

Component	Methods	Goal
Time series analysis	quantitative	Forecasting short-term trends and assessing risks and stability (Döring, 2023).
Strategy and risk management analysis	qualitative & quantitative	Identification and assessment of uncovered risks (Yin, 2018).
Sentiment analysis	qualitative & quantitative	Public perception and market sentiment assessment (Pfaffenberger, 2016).

Source: own elaboration

Time series analysis predicts short-term stock trends and evaluates historical stability by calculating volatility metrics like Value-at-Risk (VaR) using EGARCH (Bollerslev, 1986; Engle, 1982, 2001; Nelson, 1991). Volatility is quantified with a 252-day rolling standard deviation, approximating one trading year and VaR at 95%, 99% and 99.9% confidence levels as detailed in Section 4.2. Strategy and risk management analysis identifies risks such as commodity and currency exposures by employing Retrieval Augmented Generation (RAG)

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to extract relevant sections from annual reports via keyword queries and semantic search (Douze et al., 2024; Edge et al., 2024; Han et al., 2025). Quantitative analysis correlates stock prices with commodity and FX quotes using Pearson correlation coefficients and linear regression to estimate beta coefficients, with cross-currency conversions applied where necessary (Bowerman et al., 2005; Gordon, 2015). Sentiment analysis uses the FinBERT model to assign scores (positive, neutral, negative) to Reddit posts and news articles, aggregated over a 7-day window with weighted averages prioritizing recent data (Araci, 2019).

These algorithms ensure analytical depth while maintaining computational efficiency, producing outputs suitable for scoring and LLM contextualization.

4.1.4 Integration into the AI-DSS

The prepared datasets that utilize $\boldsymbol{D_k}$ serve dual purposes, as noted in Section 3.2.5. In the scoring layer (Section 3.2.3), datasets are processed using the scoring function $S_k = \beta_k(D_k, C_k)$ to generate category-specific scores, with weights w_k adjusted to reflect the investor's risk preference P and MiFID II requirements. Simultaneously, the datasets, along with scores S_k, total score S_{total} and risk preference P, are passed to the output layer (section 3.2.4) for LLM-based contextualization, as formalized by $R = LLM(\{O_k\}_{k\in K}, S_{total}, P, ISIN, \theta)$. In the formula $R = \mathrm{LLM}(\{O_k\}_{k\in K}, S_{\mathrm{total}}, P, \mathrm{ISIN}, \theta)$, R represents the final investment report in PDF format, $\{O_k\}_{k\in K}$ denotes the category-specific outputs (e.g., fundamental data, sentiment analysis) for each analysis category $k \in K$, S_{total} is the total score derived from weighted category scores, P is the conservatively determined investor risk preference, ISIN is the unique securities identifier, and θ is the configuration of the LLM. The structured formats, such as time-series matrices and categorical sentiment score, ensure compatibility with both scoring and LLM processing, with cross conversions enhancing consistency in financial data interpretation.

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Table 4 presents each component, detailing the underlying variables along with a brief description and scale level.

Table 4: List of variables

Component	Variable	Description	Scale Level
Time Series Analysis	Stock Prices	Analysis of stock prices for predicting short-term trends and identifying trading patterns.	Metric
	Trading Volume	Evaluation of trading volume to detect trading activities and predict market trends.	Metric
	Price Volatility	Assessment of price volatility to determine the stability and risk associated with stocks.	Metric
Strategy and Risk Management analysis	Stock Prices	Analysis of stock prices in relation to their correlation with various risk factors such as commodity prices, to assess strategic risk potential.	Metric
	Commodity Prices	Evaluation of commodity prices, especially relevant for companies involved in commodities, to assess commodity risk.	Metric
Sentiment Analysis	Company News Sentiment	Sentiment analysis of company news to gauge public perception and potential market impacts.	Ordinal
	Social Media Sentiment	Sentiment analysis of social media to evaluate consumer and investor sentiment.	Ordinal

Source: own elaboration

In summary, the data collection and preparation phase transforms heterogeneous datasets into structured, analysis-ready formats, enabling the AI-DSS to deliver comprehensive, MiFID II-compliant investment reports. Sequential data retrieval, rigorous cleaning, normalization, and tailored algorithms, including EGARCH, RAG, and FinBERT, ensure data quality and alignment with the investor's risk preferences. e handling of FX data through cross-currency conversions addresses the absence of direct trading pairs, and enhances analytical

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consistency. The prepared datasets support quantitative scoring in the scoring layer and contextualization in the output layer of the LLM, facilitating a robust, investor-centric decision support process.

The next section details specific algorithms in the AI-DSS, highlighting the statistical analysis in its approach.

4.2 Conceptual Operationalization and Analytical Implementation

The development is based on standardized Python libraries for math, statistics, and AI for a reliable and reproducible analysis. The aim is to create a modular, scalable, and regulatory-compliant architecture for personalized investment reports. This section states the interaction between the architectural design, the technology stack, and the operational strategy used.

4.2.1 Implementation Environment and Framework

The AI-DSS leverages a modern, scalable technology stack, as outlined in the architecture from Section 3 and the data collection and preparation described in Section 4.1 the AI-DSS leverages a modern, scalable technology stack. The technology stack is shown in a simplified manner in Figure 9: The frontend, built with React and Vite, provides an interface for input collection and report delivery, using HTTP requests to communicate with the backend. The backend, implemented with FastAPI, supports asynchronous processing of REST/JSON requests for data retrieval and analysis. Data processing is managed by Pandas and custom modules, while external APIs (e.g., LSEG, SERP, Reddit) provide access to various data sources (see also Section 4.1.1). The system includes an MAS and an LLM in the output layer to generate context-aware investment reports, with the LLM configured to produce regulatory-compliant outputs.

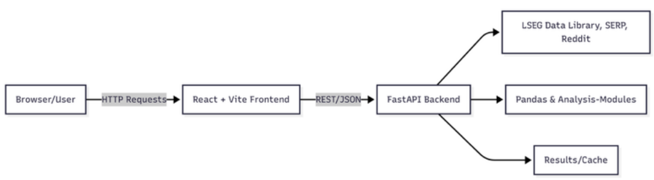

Figure 9: Implementation Environment (without architectural layers)

Source: own elaboration

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Clear separation of concerns across layers (Figure 10) achieves the system's modularity, while standardized interfaces (e.g., REST/JSON, API retrieval mechanisms) ensure interoperability. Scalability is supported by FastAPI's asynchronous capabilities and the distributed nature of the MAS, which parallelizes category-specific processing. Regulatory compliance is embedded in the conservative risk profiling logic and weighted scoring mechanism, aligning with MiFID II's investor protection requirements. Caching mechanisms in the data analysis or scoring layers improve performance by storing frequently accessed datasets or scores.

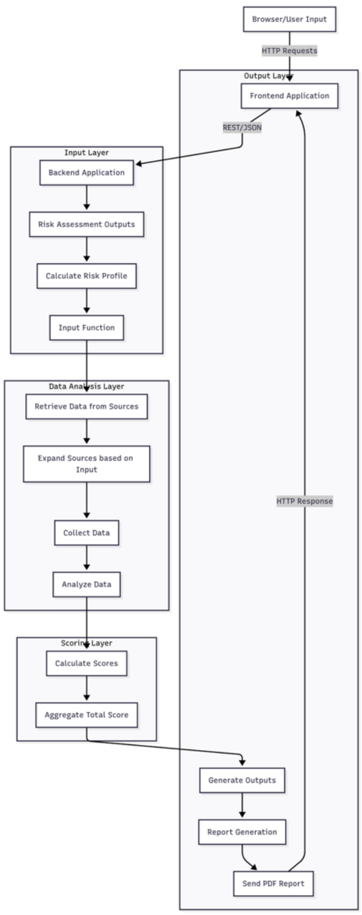

Figure 10: Technical Process for Creating Individual Investment Reports

Source: own elaboration

The sampling strategies detailed in Section 4.1.1 serve as the foundation for the analytical methods supported by the technical implementation of the AI-DSS discussed in this section. Additionally, the three main algorithms utilized within the AI-DSS are described. While EGARCH-VaR evaluates quantitative risks, sentiment analysis offers qualitative insights into public perception. In contrast to this, RAG and regression analysis are employed for hedging strategy validation, as explained in the following section.

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4.2.2 Volatility-based Risk Quantification utilizing EGARCH-VaR-Models

The Value-at-Risk (VaR) plays a significant role in decision making process for investment portfolios. It measures the estimated maximum loss of a portfolio over a specific time horizon, with a confidence level of $1 - \alpha$. It represents the loss that is not expected to be exceeded with a probability of $1 - \alpha$ (e.g., 95% confidence level means a 5% chance of exceeding the VaR). VaR is also referred to as 'Earnings at Risk,' 'Money at Risk,' or 'Capital at Risk' in some contexts (Dowd, 2002; Jorion, 2006; Olson & Wu, 2010).

To calculate this measurement, it is crucial to determine whether the risk factor applies to the entire investment portfolio or only a specific component. Additionally, it is necessary to ascertain if the value of an asset, or changes within an asset's value, can be classified as a risk. Furthermore, one must clarify whether empirical or parametric models will be utilized (Steiner et al., 2017). An empirical model relies on historical data or subjective expectations, whereas a parametric model assumes that profits and losses follow a specific distribution, such as a normal distribution or student-t-distribution (Abad et al., 2014). Recent studies have examined the historical simulation approach and determined that this empirical method does not always provide accurate risk metric estimations (Abad & Benito, 2013; Danielsson & De Vries, 2000). More commonly, parametric approaches are used, which involve fitting probability curves to the data and then inferring the VaR from these fitted curves (Abad et al., 2014).

In practice, parametric models are chosen based on the nature of the input data and the desired granularity of the risk analysis, enabling the system to tailor its approach to the specific characteristics of each investment scenario (Steiner et al., 2017). For the purposes of the described AI-DSS, an EGARCH-VaR model will be implemented. These models are utilized as a parametric approach to calculate risk measurement and enable precise quantification of market volatility, thereby providing investors with robust risk assessments (Abad et al., 2014; Abad & Benito, 2013; Bollerslev, 1986; Engle, 1982; Michańków et al., 2023; Müller & Righi, 2024).

The Exponential GARCH (EGARCH) model, which is employed within the AI-DSS, is derived from the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) framework, which itself is an extension of the Autoregressive Conditional Heteroscedasticity (ARCH) model. The ARCH model features a variance over time (Engle, 1982). The GARCH model enhances this framework by introducing a generalized approach that estimates two equations: one depicting the evolution of returns based on historical returns and another modeling the changing volatility of those returns (Bollerslev, 1986).

The EGARCH model enhances the GARCH framework by modeling the logarithm of the conditional variance, ensuring that the variance remains positive without requiring parameter constraints. Unlike the standard GARCH model, EGARCH captures asymmetric effects, allowing positive and negative shocks to impact volatility differently. This is particularly useful in financial markets, where negative shocks often lead to larger volatility increases than positive shocks of the same magnitude. The EGARCH model's ability to account for this leverage effect makes it a powerful tool for the AI-DSS in analyzing and forecasting financial time series data (Nelson, 1991).

The model offers a sophisticated and reliable approach for estimating VaR for equities, as it effectively models time-varying volatility and accounts for asymmetric market responses to shocks. By modeling the conditional variance of stock returns, EGARCH enables the AI-DSS to compute VaR with greater precision, particularly in turbulent market conditions where downside risks are more pronounced. This capability enhances risk management by offering more reliable estimates of the potential downside risk in stock portfolios, allowing investors to make informed decisions to mitigate losses (Jorion, 2006).

A simulation of a stock portfolio over 500 days, using returns generated from a t-distribution to reflect fat-tailed market behavior, demonstrates the effectiveness of the EGARCH model in the AI-DSS (see also Figure 11). The simulation uses a portfolio worth €1,000,000, a theoretical expected daily return of 0.02% (though the fitted model predicts a small loss, as explained below), and a daily volatility of 1%. The EGARCH(1,1,1) model shows an asymmetry parameter of 0.1547, which means that negative shocks make volatility rise more than positive shocks, which is how the leverage effect works (Nelson, 1991).

Figure 11 illustrates the simulated portfolio returns (blue) in comparison to VaR estimates, underscoring the EGARCH model's dynamic adaptation to volatility. Backtesting results further corroborate this methodology: at a 99% confidence level, the EGARCH-VaR model records 2 exceedances compared to an anticipated 5, outperforming the parametric VaR's 3 exceedances and demonstrating superior precision under volatile conditions. The model is configured with a fitted mean return of -0.017339% (a slight daily loss differing from the theoretical 0.02% due to realized returns), a baseline volatility of 0.112931, an ARCH effect of -0.060639 (indicating that past shocks slightly reduce future volatility), an asymmetry

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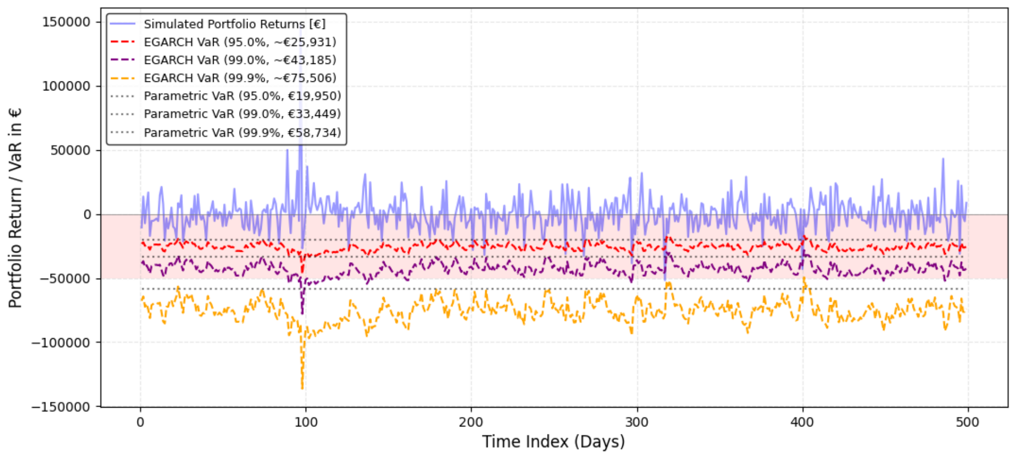
effect of 0.154650 (showing that bad news increases volatility more), a persistent volatility effect of 0.747879 (indicating that 75% of prior volatility carries over), and a fat-tail parameter of 4.999365 (which allows for extreme market moves). Backtesting shows 2 exceedances at 99% confidence (compared to the expected 5 and the parametric VaR's 3) and no exceedances at a 99.9% confidence level (compared to an expected value of 0.5, matching parametric VaR's result of 0). At a 95% confidence level, the EGARCH model exhibits conservative performance with only 8 exceedances versus 25 expected, indicating a prudent risk estimation that is advantageous for risk management. These results, visualized through a comparison of EGARCH and parametric VaR against simulated portfolio returns, underline the model's ability to provide robust and reliable risk assessments and, thus, support informed investment decisions (Abad & Benito, 2013).



Parameter	Value
Portfolio Value	€1,000,000
Expected Return (μ)	0.02% daily
Volatility (σ)	1% daily
Simulation Horizon	500 days
VaR Confidence	95%, 99%, 99.9%
VaR Models	Parametric (t-dist), EGARCH(1,1,1)
Returns	Log returns (%)
EGARCH Dist.	t-distribution
Asymmetry Parameter	0.1547

Figure 11: Comparison Parametric vs. EGARCH-based VaR

Source: own elaboration

Next, sentiment analysis is discussed, which complements quantitative analyses with qualitative insights from public data sources.

4.2.3 Sentiment-Analysis utilizing FinBERT for Financial News

Sentiment analysis leverages targeted data from social media, such as Reddit, to evaluate public perception of a company and integrate these insights into decision-making (Pfaffenberger, 2016). There are multiple methods to conduct an analysis for data that is either nominal or ordinal. The following techniques provide details on how to put computational research into practice in the area of text and content analysis. These include using procedures

1) based on dictionaries,
2) machine learning methods that are either supervised,
3) or machine learning methods that are unsupervised (Döring, 2023, p. 1025 f.).

An often-used method for procedures based on dictionaries is an automated sentiment analysis. This analysis method utilizes dictionaries and attempts to determine whether the overall tone of a text is negative or positive (Liu, 2020). The analysis outcome relies on emotions communicated either directly or indirectly. Therefore, the number of negative and positive associations was counted and divided by the number of words in the text (Wu, 2021). Within an advanced analysis, the text can be classified as excellent, acceptable, average, poor, or very poor. To perform the analysis, the dictionary must be reviewed and modified to match the data being analyzed (González-Bailón & Paltoglou, 2015).

Another way to analyze data is through machine learning methods that are supervised. This technique requires a training and test dataset while an algorithm performs the classification process. The provided information can be sorted into a dependent variable (positive or negative classification) and an independent variable (the given text) (Wiegand et al., 2019). After the first categorization is finished, the results will be reviewed, and the algorithm may be adjusted to improve accuracy. Various methods like Naive Bayes, support vector machines, logistic regression and decision trees are potential options (Döring, 2023). For this research project, it is possible to test different classification models and select the most suitable one, evaluated by the quality criteria.

The last approach describes machine learning methods that are unsupervised. The difference between this approach and the previous ones is that this approach is inductive, i.e. it doesn't require a training/test data set or a dictionary. Instead, this method directly engages with the text data, automatically seeking correlations or patterns within the provided data set. After the identification process, the results are revised and related back to the research questions (Döring, 2023). Common algorithms are structural topic models (Wang et al., 2011), bi-term topic modeling (Yali et al., 2014) and latent Dirichlet allocation (Maier et al., 2018).

To summarize, all three methods can be utilized for sentiment analysis within the data analysis core. For this research project, a specific approach known as FinBERT (Araci, 2019) -

well-regarded in financial research - is employed in the AI-DSS. FinBERT focuses on supervised learning models as previously described. This model is trained on financial data to classify a given phrase as positive, neutral, or negative. It is developed as a transformer-based framework (BERT) and outperforms approaches such as Support Vector Machines and Naive Bayes (Araci, 2019; Devlin et al., 2018). The FinBERT model is specifically trained on financial data, enabling it to make accurate classifications within the financial context. In the realm of investment reporting, FinBERT serves as an effective tool for determining market sentiment. It classifies social media posts, such as those found in Reddit communities, as well as financial news, into positive, neutral, or negative categories.

Reddit constitutes a high-frequency, discourse-centric platform with structured, subreddit-based communities that enable targeted sampling and topic-focused analysis, as exemplified by potentially relevant subreddits such as r/personalfinance (2.3 million visitors and 25,352 contributions per week, 21.4 million subscribers as of November 2025), r/stocks (1.1 million visitors and 15,432 contributions per week, 9 million subscribers as of November 2025), and r/wallstreetbets (3.2 million visitors and 157,040 contributions per week, 20 million subscribers as of November 2025). Yet it demands careful handling to ensure scientific soundness. Data quality benefits from moderation and clear metadata (threads, timestamps, engagement), while acknowledging that moderation choices can introduce subjective biases (Adams, 2024). Representativeness is limited - user demographics skew younger, tech-savvy, and male - so findings require appropriate caveats and, where possible, weighting or triangulation with other data sources such as alternative social media platforms (e.g., X/Twitter or Facebook) or traditional news outlets, as implemented in this thesis (Chi & Chen, 2023). Observable biases include selection bias, popularity/upvote bias, and herding; mitigation applies engagement-weighted aggregation, deduplication, horizon constraints, and identifier validation (company name variants, ISIN, ticker/RIC). Accordingly, Reddit sentiment is treated as complementary and combined with news-based sentiment from DS_{LSEG}.

The next section depicts risk assessment in combination with quantitative analysis and qualitative insights from public data sources.

4.2.4 Strategy and Risk management analysis with RAG and Regression Models

The strategy and risk management analysis focuses on company data, such as annual reports, to identify uncovered risks. A statistical regression is used to verify the coverage of a specific risk. Therefore, the company's stock prices, commodity prices and strategic risk factors are analyzed using a statistical regression model, such as multiple linear regression. In case of a good coverage, there wouldn't be a significance of commodity prices and strategic risk factors with the stock of the company. If there is a correlation between one of these factors and the stock price, it can be assumed that the given risk is not covered by the company's risk management. Even a small correlation between commodity prices or strategic risk factors and the company's stock price indicates a potential dependency that could pose a risk, as it suggests incomplete coverage by the company's risk management. Quantifying "good coverage" is challenging, as any statistically significant correlation, regardless of magnitude, may point to an uncovered risk that requires further investigation.

The validation process is aligned with a structured workflow as depicted in the corresponding flowchart (Figure 12). The process systematically integrates data acquisition, extraction, and analysis to assess hedging strategies: start is the acquisition of annual reports from external sources via SERP API, followed by text segmentation and semantic indexing using a vector store to enable efficient data retrieval.

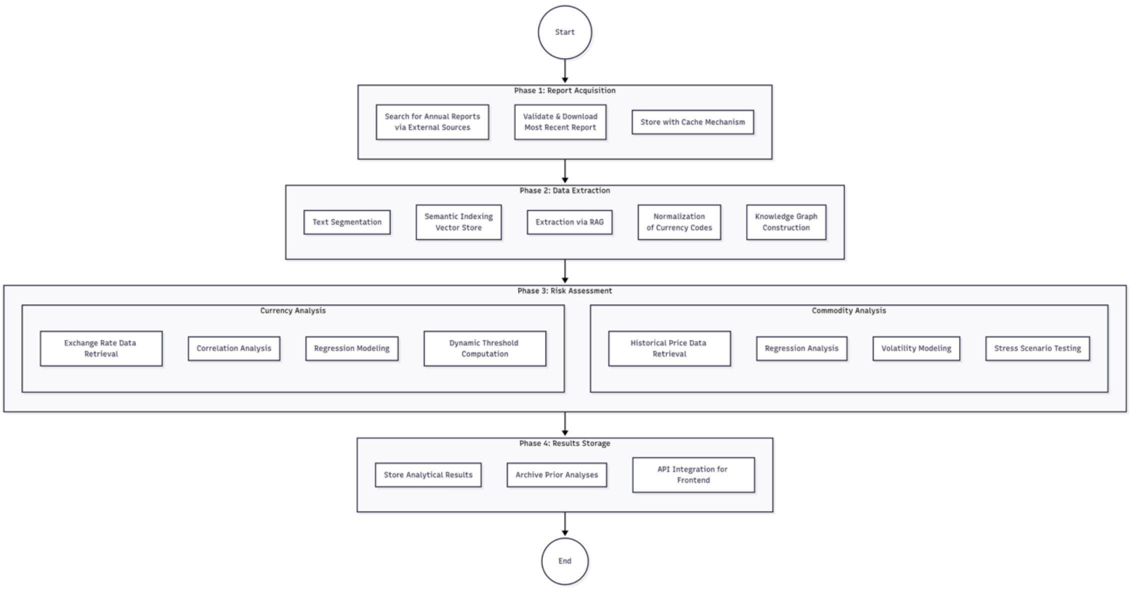


Figure 12: Process of the Risk assessment within the AI-DSS

Source: own elaboration

RAG allows for the extraction of relevant information, such as commodity and currency exposures, which is then normalized and organized into a knowledge graph. This graph informs the risk assessment phase, where regression analyses, volatility modeling, and stress scenario testing are used to quantify the impact of commodity and currency fluctuations on

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stock prices. Results are stored, archived, and made accessible via API integration, ensuring traceability and usability.

This systematic approach, combining advanced computational techniques with statistical methods, aims to enhance the accuracy and comprehensiveness of the hedging strategy validation.

5 DEMONSTRATION AND EVALUATION

The Demonstration and Evaluation chapter is structured into three sections. First, the type of demonstration conducted will be outlined, indicating how the artifact addresses the stated problem. Next, the evaluation framework will be detailed. The evaluation follows two methods: a framework analysis that compares actual investment reports to those generated by the AI-DSS based on predefined criteria and a quantitative questionnaire in which 20 financial experts assess the AI-generated investment report. The discussion chapter then synthesizes both sets of findings to summarize the extent to which the artifact addresses the identified problem.

5.1 Demonstration

The AI-DSS is demonstrated in a comprehensive field study that thoroughly illustrates the practical applicability of the artifact for effectively reducing information asymmetries in the complex financial market ecosystem. The AI-DSS system is meticulously applied to a specifically selected company that strategically operates as both a manufacturing and a trading company, specifically the renowned automobile manufacturer Mercedes-Benz, which is precisely identified by its unique International Securities Identification Number (ISIN) for accurate tracking and analysis. The deliberate selection of this company is strategically based on several critical factors: its significant market relevance in the global economy, the exceptional availability of comprehensive financial and sentiment data across multiple platforms, and its established importance and influential position in the automotive industry. These selection criteria collectively enable researchers to thoroughly test and evaluate both the robustness and versatility of the AI-DSS system under real-world market conditions with a company that presents multifaceted analytical challenges.

In the field study, an investment report is output as a product of the AI-DSS with a preselection of manual entries such as ISIN or risk preference. A risk-neutral investor profile serves as an example to illustrate the system’s functionality for an average investor, balancing risk avoidance and return objectives. Accordingly, the MiFID questionnaire is completed from the perspective of a risk-neutral investor. This results in responses indicating risk neutrality in both Part 1: Risk Tolerance (see Figure 13) and Part 2: Risk Willingness (see Figure 14).

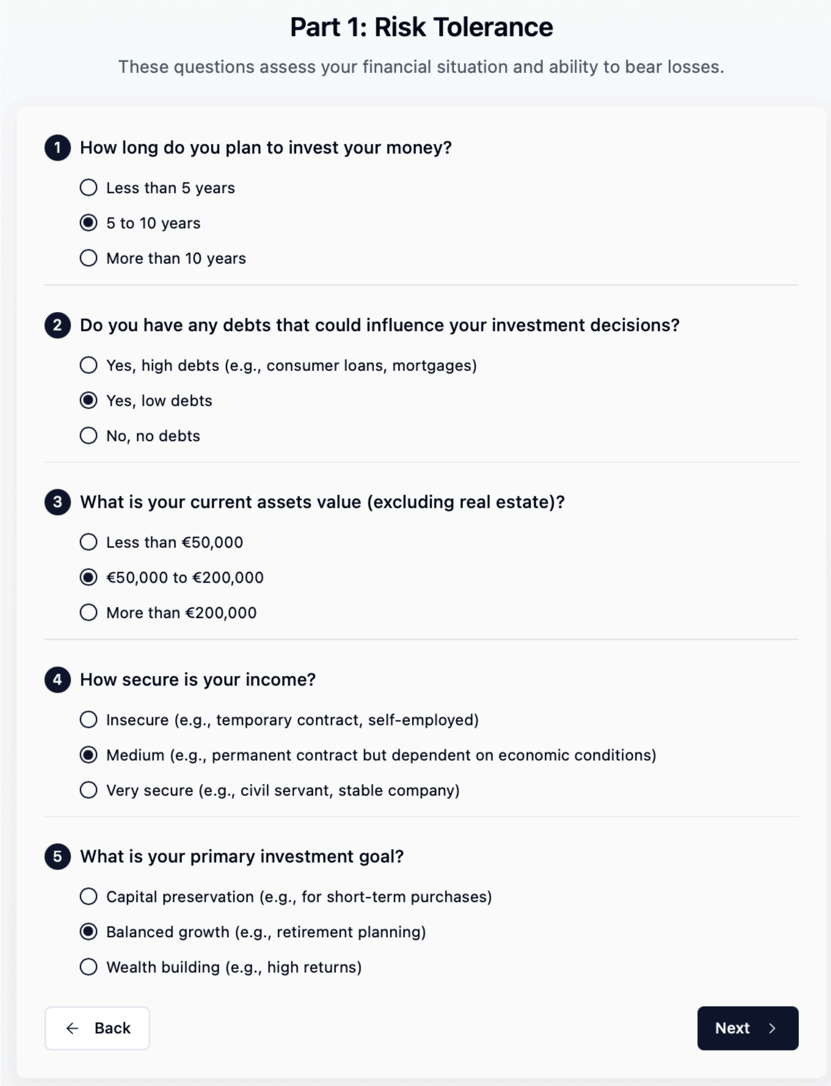

Figure 13: Part I: Risk Tolerance

Source: own elaboration

The preselected responses in Figure 13 were chosen to simulate a risk-neutral investor's financial situation, balancing medium-term investment horizons, moderate debts and balanced goals to reflect a moderate ability to bear losses without excessive conservatism or aggressiveness.

Figure 14: Part II: Risk Willingness

Source: own elaboration

The preselected responses in Figure 14 were chosen to represent a risk-neutral investor's willingness to take risks, emphasizing a balance between security and returns, moderate reactions to losses and acceptance of limited fluctuations to align with a neutral risk willingness. This complements the tolerance assessment and leads to the overall scoring.

Each response is assessed using the scoring function outlined in section 3.2.1 resulting in the classification of a risk-neutral investor that complies with MiFID regulations (Richter, 2018), see Figure 15.

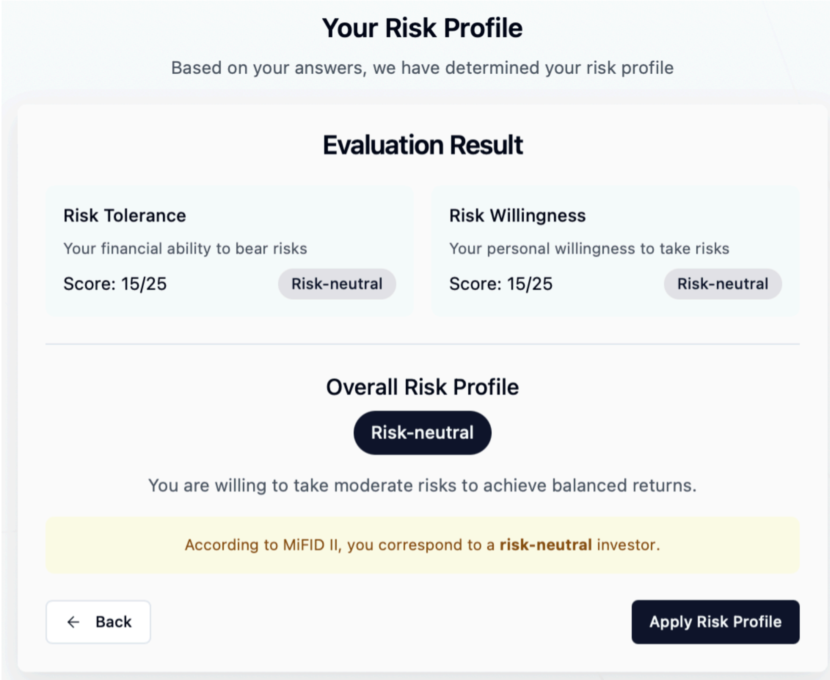

Figure 15: Part III: Individual Risk Profile

Source: own elaboration

The overall profile in Figure 15 results from preselected responses designed to demonstrate a risk-neutral classification, combining moderate tolerance and willingness to illustrate balanced risk-return preferences in compliance with MiFID II. This profile serves as the basis for the subsequent data processing in the AI-DSS, where the risk-neutral score is integrated with company-specific inputs.

After entering the specific ISIN of Mercedes Benz Group AG (DE0007100000) and the overall risk score (risk-neutral) the AI-DSS accesses a heterogeneous database that includes financial data from the LSEG API, raw data for sentiment analysis from the Reddit API, and information from company websites and documents (e.g. annual reports). The data analysis core applies established methods: time series analysis of stock prices and volatility is performed using, e.g., EGARCH, where risk management analysis uses multiple linear regression; and public perception is assessed using NLP-based sentiment analysis. A scoring model weights the results of these analyses to produce an overall valuation score for the individual stock that considers the risk-neutral perspective.

The output layer of the AI-DSS then generates an individual investment report for Mercedes-Benz, which is specifically crafted as an illustrative example for a risk-neutral investor pro-

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file. This comprehensive report contains detailed and methodically calculated risk assessments designed to support informed decision-making processes, complemented by a transparent and thorough presentation of the underlying analytical methodologies and findings. The report systematically incorporates various data visualizations and analytical results - including time series analyses with trend interpretations, comprehensive risk evaluation metrics with appropriate confidence intervals, and sentiment analysis results drawn from multiple online sources to provide a balanced perspective. Each analytical component is presented with appropriate context to ensure the investor can fully understand both the significance and limitations of the provided information.

This structured report serves as the core artifact of the AI-DSS, demonstrating how it synthesizes complex data into actionable insights; see Figure 16.

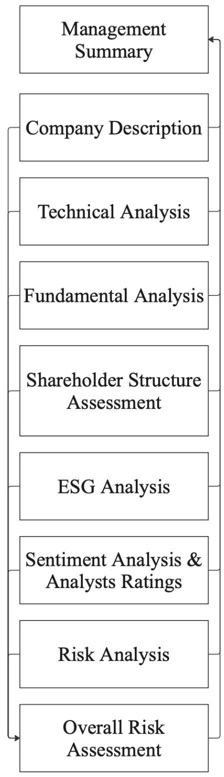

Figure 16: Structure of the Report

Source: own elaboration

In the following, the nine sections of the investment report are outlined in detail to showcase the system's comprehensive and user-centric design. A full sample report generated by the AI-DSS, closely corresponding to the structure and logic of the report used in the empirical

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analysis, is provided in Appendix IV. All company-specific or licensed information has been anonymized where required.

1. A comprehensive *management summary* offers guidance on the principal findings of the investment report. Key highlights are outlined and appropriately referenced to their respective chapters, with the overall scoring prominently displayed at the beginning of the summary.
2. The first chapter presents the *company description*. It outlines the business model and strategy, explains the market position with information on shareholder analysis, and provides an overview of the overall risk classification.
3. The following chapter provides a comprehensive *technical analysis*, including a concise time series and an in-depth examination of the stock's volatility. All visuals are thoroughly contextualized to enhance understanding. Key performance indicators are discussed in relation to varying risk preferences. Additionally, the stock's volatility and volume volatility are analyzed and classified according to risk-seeking, risk-neutral, and risk-averse categories. The primary objective is to determine the overall risk classification based on these metrics.
4. Following this, *fundamental analysis* is conducted. The company is evaluated using both historical and projected growth metrics to provide a comprehensive assessment of its performance. For a more in-depth examination, sections on profitability ratios, liquidity ratios, solvency ratios, efficiency ratios, and additional growth indicators are presented and analyzed in context with respect to individual risk preferences.
5. Following both technical and fundamental analysis, a *shareholder structure assessment* is conducted. The primary shareholders are identified, detailing their respective ownership percentages and classifications, such as private companies or institutional investors. Subsequently, the ownership structure provides an overview of share distribution and free float. These findings are then analyzed and contextualized in relation to the specific risk preferences indicated at the input stage.
6. The *ESG analysis* offers a thorough evaluation of the company's environmental, social, and governance performance. The assessment begins with an overall rating, followed by detailed category breakdowns that include specific scores and notations. Historical trends are presented through a timeline chart, while risk levels in each category are systematically evaluated. Actionable recommendations are provided,

tailored to the investor’s risk profile, emphasizing balanced opportunities and continuous monitoring. A concise bullet-point summary further underscores the company's suitability for stability-oriented investments.

7. The *sentiment analysis and analyst ratings* section assesses the company's public perception from financial news and social media, detailing the methodology using NLP models like FinBERT to categorize sentiments into positive, neutral and negative, presenting 7-day sentiment data in tables and charts for distributions across platforms, followed by analyst recommendations categorized by strong buy, buy, hold, sell and strong sell with an average rating, target prices including average, highest and lowest values, actionable recommendations tailored to the individual risk preference suggesting a cautious strategy with potential opportunities and a bullet-point summary emphasizing stability and moderate upside potential aligned with the investor's risk profile.
8. The *risk analysis* section provides an overview of the company’s risk situation, detailing key metrics such as daily and annual returns, volatility, Sharpe and Sortino ratios, maximum drawdown, and Value at Risk; outlining the methodology for commodity exposure analysis using knowledge-graph technology and volatility modeling; presenting risk indicators in tables; analyzing hedging effectiveness for currencies and commodities with exposure percentages; offering recommendations for diversification and hedging strategies; and concluding with actionable advice emphasizing portfolio review, market monitoring, and professional consultation.
9. The *overall risk assessment* section combines various risk metrics into a total score representing the asset's risk evaluation, introducing the assessment as a tool for understanding risk-return balance with a moderate category score, detailing the methodology with six weighted categories including volatility, volume, performance, sentiment, ESG and hedging, analyzing detailed category scores and main risk drivers, providing visualizations and subcategory descriptions, defining risk categorizations based on score ranges, offering actionable recommendations for investors and summarizing the total score, methodology and multi-step calculation process.

Together, these nine sections provide a clear overview of whether the company aligns with investors' risk preferences. This field study thus comprehensively demonstrates the sophisticated capability of the AI-DSS to generate accurate, reliable, and transparent investment recommendations that effectively reduce information asymmetries between market participants. Furthermore, this practical application successfully fulfills the stringent requirements of the demonstration step of the DSR methodology, validating both the functional efficacy and the practical utility of the developed artifact in real-world investment scenarios.

By structuring the demonstration and evaluation process in this manner, the study ensures that both the functionality and the real-world applicability of the AI-DSS are rigorously assessed through empirical evidence and expert validation. This comprehensive approach enables researchers to verify the system's performance across various financial scenarios and market conditions, while simultaneously gathering feedback from domain experts who can identify nuanced aspects that purely quantitative methods might overlook. The interplay between quantitative and qualitative approaches not only strengthens the credibility of the findings but also allows for the identification of strengths and potential areas for improvement in the system's design. Quantitative measures provide objective performance metrics, while qualitative assessments capture the subjective experiences and insights of potential users, creating a more complete evaluation framework (Döring, 2023). This dual-pronged strategy provides a holistic view of the artifact's impact, bridging the gap between theoretical development and practical deployment in the financial domain. By examining both technical efficacy and user-oriented value, the evaluation captures the multifaceted nature of the system's contribution to decision support in investment contexts, ultimately demonstrating its potential to transform how investors navigate complex financial landscapes.

5.2 Evaluation

To ensure validity and reduce systematic bias in the evaluation of the AI-DSS, this section applies a methodological triangulation based on a combination of qualitative and quantitative approaches (Denzin, 2017; Flick, 2011). This strategy integrates an objective framework analysis with an expert questionnaire to cover both output-based criteria such as risk adjustment and transparency as well as perceptions of information asymmetries (see Figure 17).

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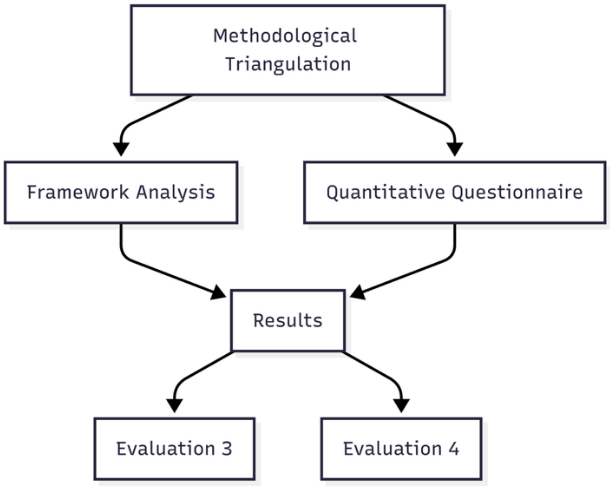

Figure 17: Methodological Triangulation

Source: own elaboration

This approach does address the research question and ensures the robustness of the artifact in accordance with DSR evaluation levels Eval 3 and Eval 4 as described in Section 3.1 (Sonnenberg & Vom Brocke, 2012; J. Venable et al., 2016). The two components of triangulation - framework analysis and quantitative questionnaire - are explained in detail below, each accounting for 15% of the research and fulfilling the requirements of the evaluation step of the DSR methodology (Peffers et al., 2007; J. Venable et al., 2016). The framework analysis aims to answer the research question by comparing the investment report generated by the AI-DSS with existing investment reports. This comparison is based on clearly defined criteria: the adaptation of the recommendations to the investor's risk willingness, the transparency of the analyses presented, the relevance of the information provided for investment decisions and the comparability with established reports. These criteria address the research question directly by examining how the AI-DSS supports investment decisions through risk-based adjustments. Furthermore, decisions are also supported by inferring the effectiveness of technical components based on report quality to reduce information asymmetries. From the DSR perspective, the framework analysis focuses on the evaluation of level Eval 3, which assesses the user-friendliness and robustness of the artifact, and also on Eval 4, which examines its effectiveness and practicality *(Sonnenberg & Vom Brocke, 2012)*.

In addition, the quantitative questionnaire serves to substantiate the hypothesis that the AI-DSS reduces information asymmetries and promotes well-founded decisions. To this end, expert feedback is collected using Likert scales, whereby the experts evaluate the targeted data analysis of the AI-DSS, the reduction of information asymmetries, the trust in the recommendations generated, and the practical relevance of the system (Lang et al., 2011; Orbán & Stefkovics, 2025). These evaluations confirm the hypothesis directly by measuring asymmetry reduction and well-founded decisions and indirectly through implications for the practicality of technical components. The questionnaire also focuses on Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness, and practical suitability of the artifact; see Table 5. The combination of these approaches ensures a comprehensive assessment of the AI-DSS that considers both objective and subjective criteria and fully meets the requirements of the DSR methodology.

Table 5: Evaluation criteria

Method	Goal	Criteria	DSR evaluation
Framework analysis	Answering the research question	Adjustment to risk willingness, transparency, relevance, comparability	Eval 3, Eval 4
Quantitative questionnaire	Underpinning the hypothesis	Targeted data analysis, reduction of information asymmetries, trust, practical relevance	Eval 3, Eval 4

Source: own elaboration

The quality criteria of the research question using the DSR methodology are ensured by comprehensive quality assurance, relevance, reliability, rigor, transparency, validity and robustness (Peffers et al., 2007). The relevance of the research project is ensured by the sound validation of the problem of information asymmetries using principal-agent theory and current literature, which underpins the practical significance for investors (Eisenhardt, 1989; Shah, 2014). Reliability is achieved through standardized methods, consistent data preparation with tools such as pandas (McKinney, 2010) and the use of high-quality data sources such as the LSEG-API, which promotes the reproducibility of the results. Rigor is achieved through the use of established methods such as EGARCH and NLP as well as a solid theoretical foundation, which underlines the scientific rigor of the AI-DSS (Araci, 2019; Bartelt & Röser, 2024a; Box, 2013). Transparency is provided by systematic documentation of all development steps, from data processing to evaluation, which enables traceable verification. The evaluation's validity is ensured by combining framework analysis with a quantitative questionnaire, along with precisely defined criteria such as adaptation to risk willingness and

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reduction of information asymmetries, which together ensure a comprehensive assessment of the artifact (Sonnenberg & Vom Brocke, 2012).

This validation directly addresses the research question by evaluating the support of decisions through risk adjustment and indirectly by deriving the role of critical technologies (e.g., data integration from heterogeneous sources) for asymmetry reduction. Finally, careful data handling, including the validation of models and the consideration of heterogeneous data sources such as the Reddit API and company documents, ensures the robustness of the AI-DSS so that reliable and robust investment recommendations can be generated.

5.2.1 Framework Analysis

The framework analysis is structured into three distinct components. First, the methodological foundations of framework analysis within the context of DSR evaluation are outlined. Next, the selection of criteria for the framework analysis, along with corresponding scoring for each criterion, is developed and detailed. Subsequently, the applied criteria matrices are analyzed and described in a comprehensive manner. This tripartite process ensures transparency throughout this phase of evaluating the AI-DSS artifact, with an emphasis on usability, robustness, effectiveness, and practical applicability.

5.2.2 Framework Analysis in DSR Evaluation

A framework analysis is conducted to compare existing investment reports with the investment report generated by the AI-DSS. Framework analysis is a qualitative approach employed to scrutinize texts from diverse sources, including scientific protocols, interview transcripts, or documents pertinent to a specific topic (Srivastava & Thomson, 2009). Qualitative framework analysis was originally developed for empirical political research (Bryman & Burgess, 2002; Ritchie & Spencer, 2002), but recently, this methodology has become commonly used in qualitative research (Gale et al., 2013; Goldsmith, 2021; Lazarus, 2022).

In scientific literature, a framework analysis often applies a fixed concept for creating a matrix (Goldsmith, 2021; Lazarus, 2022; Parkinson et al., 2016; J. Smith & Firth, 2011). This concept encompasses the steps of familiarization, framework identification, indexing, charting, and mapping & interpretation, all of which aid in data organization and promote transparency in the research process.

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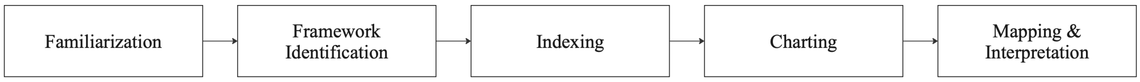

Figure 18: Process of a scientific framework analysis

Source: Adapted from Goldsmith (2021); *own elaboration*

The logical sequence, outlined in Figure 18, is briefly described in the following paragraphs and will be further applied in Section 5.2.2.1 with respect to the selection of criteria for framework analysis.

I. Familiarization: In this phase, the focus is on analyzing the provided material and reading it several times. This approach helps the researcher better understand the structure of the content and identify any particular features or key messages (Ritchie & Spencer, 2002).

II. Framework Identification: The next phase involves identifying repetitive content and topics within the materials. Based on this analysis, it is possible to define key and subtopics or establish categories and criteria (Ritchie & Spencer, 2002).

III. Indexing: In this phase, identified topics are supported with relevant text excerpts, such as paragraphs from the provided material, to clarify the key topics and subtopics established in the previous phase (Ritchie & Spencer, 2002).

IV. Charting: The primary objective of this phase is to construct the chart. At this stage, categories and criteria must be determined and finalized. Each key topic or category can be systematically analyzed within an individual chart, with citations added to the cells to accurately illustrate how each category is addressed. The final step involves integrating all separate charts into a comprehensive chart encompassing all relevant information (Ritchie & Spencer, 2002).

V. Mapping & Interpretation: This phase involves analyzing the entire material. Analysis may be conducted by examining each category and its criteria or by focusing on similarities and differences (Ritchie & Spencer, 2002).

Applying this concept allows researchers to meet the central requirements for scientific quality in framework analysis, especially concerning validity and objectivity (Flick, 2020). In addition to taking into account fundamental qualitative quality criteria such as methodological fit, intersubjectivity and reflexivity, a particular focus is on ensuring transparency and traceability throughout the entire analysis process, which is carried out on an empirical basis (Dunger & Schnell, 2018).

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5.2.2.1 Criteria Selection for the Framework Analysis

As previously described, the framework analysis employs an established model to systematically examine existing investment reports and compare them with artifacts generated by the AI-DSS. The criteria for this analysis are developed deductively based on the research questions and relevant theoretical frameworks, including principal-agent theory, which examines information asymmetries between investors and companies, as well as the provided materials, such as various investment reports. This deductive approach utilizes four categories - transparency, alignment with risk willingness, relevance and completeness and efficiency and practicability - to evaluate how the AI-DSS supports risk-based investment decisions and to analyze the function of technological components in addressing information asymmetries. These categories were each specified with different subcategories, known as criteria. For each criterion a weight is assigned to determine the importance regarding the research project. Nine of these criteria are weighted equally at 10%, reflecting their equal importance in this research project. Additionally, two other criteria included in the evaluation, while not directly related to the research questions and hypothesis, receive lower weights of 5% each in the framework analysis.

These criteria and weightings are used for a comparative analysis between the AI-DSS report on Mercedes-Benz Group AG (28.07.2025) and eleven other analyst reports, with the aim of answering the research questions of the DSR project and verifying the hypothesis. The criteria are organized into transparency, alignment with risk willingness, relevance and completeness, and efficiency and practicability. This approach provides a structured and objective means of evaluating report quality as depicted in Table 6**.**

Table 6: Evaluation Criteria for framework analysis of investment reports

Category	Criterion	Description	Rating	Weighting (in %)
Transparency	1.1 Clarity and comprehensibility	Assesses whether the report (e.g., share price analysis, ESG, fundamentals) is clear, precise and understandable for investors without in-depth specialist knowledge.	1 (very unclear) to 5 (very clear)	10

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Category	Criterion	Description	Rating	Weighting (in %)
Transparency	1.2 Disclosure of risks and uncertainties	Checks whether the report transparently presents potential risks (e.g., decline in profitability, market volatility) and uncertainties in order to strengthen investor confidence.	1 (no disclosure) to 5 (full disclosure)	10
Transparency	1.3 Comprehensibility of the recommendation	Evaluates whether the investment recommendation is justified by analyses (e.g., fundamental data, ESG) and appears comprehensible. This reduces asymmetries by providing a clear basis for decision-making.	1 (not comprehensible) to 5 (very comprehensible)	10
Adjustment to risk willingness	2.1 Consideration of risk profiles	Evaluates whether the report provides analyses (e.g., volatility, beta, risk assessment) that are relevant for risk-averse, risk-neutral or risk-sensitive investors.	1 (no consideration) to 5 (strong consideration)	10
Adjustment to risk willingness	2.2 Individualized decision support	Checks whether the report provides customized recommendations or information tailored to specific risk willingness rather than making general statements.	1 (not individualized) to 5 (highly individualized)	10
Adjustment to risk willingness	2.3 Flexibility of the analyses	Assesses whether the report integrates different perspectives (e.g., short-term vs. long-term risks, ESG vs. financial stability) to cover different investor preferences.	1 (no flexibility) to 5 (high flexibility)	10
Relevance and completeness	3.1 Completeness of the analyses	Checks whether the report covers all relevant aspects (e.g., share price, ESG, fundamentals, shareholder structure, performance metrics).	1 (very incomplete) to 5 (very complete)	10
Relevance and completeness	3.2 Relevance for investment decisions	Evaluates whether the information provided (e.g., profitability decline, ESG score) is relevant for informed investment decisions.	1 (not relevant) to 5 (very relevant)	10
Relevance and completeness[1]	3.3 Integration of different data sources	Checks whether the report integrates various data sources (e.g., market data,	1 (no integration) to 5	5

[1] Overall weighting: 100%. Criteria 3.3 and 4.2 receive lower weightings because they are relevant for future research but not central to the research questions. Assessments are made subjectively by the researcher in accordance with the objectives set at the beginning of the work.

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Category	Criterion	Description	Rating	Weighting (in %)
		sustainability data, shareholder data) to provide a holistic picture.	(strong integration)	
Efficiency and practicability	4.1 User-friendliness	Checks whether the report is easily accessible, well-structured and practical for investors (e.g., clear tables, clear sections).	1 (not user-friendly) to 5 (very user-friendly)	10
Efficiency and practicability3	4.2 Practical suitability	Evaluates whether the report can be used directly for investment decisions or portfolio management.	1 (not suitable for practical use) to 5 (very suitable for practical use)	5

Source: own elaboration

5.2.2.2 Description of the Investment Report Provider and Evaluation due to the given criteria.

Following the evaluation criteria from the previous section the methodology is applied to eleven distinct investment reports from professional analysts and financial institutions. Due to the varying license agreements of each publisher, these reports are referred to anonymously as Report 1 through Report 11. To address this, generalized descriptions of each report provider and methodological approach are provided below, ensuring transparency even with accordance to the corresponding license agreements:

- Report 1: An international provider of algorithm-based multi-factor analyses for stocks, sectors, portfolios, and entire markets. The underlying models integrate key figures from the areas of earnings, fundamentals, valuation, momentum, risk and insider trading trends. Structured investment reports present the analysis results, incorporating peer comparisons and automatically generated text modules to derive data-based action recommendations.
  The sample report analyzed comprises 11 pages and refers to a single stock.
- Report 2: A German research provider specializes in investment reports utilizing a proprietary scoring system to evaluate analyst opinions, growth, profitability, and risk through a unified metric. The approach emphasizes fundamental analysis alongside value investing principles. The primary objective is to offer a curated selection of high-growth individual stocks.

The sample report reviewed spans 31 pages and focuses on the analysis of a single stock.

- Report 3: A financial services provider based in the Mediterranean region with decades of experience and licensed by the national financial supervisory authority produces research publications for private and institutional investors. Traditional fundamental analysis and individual consulting approaches form the basis of the reports, and the assessment also incorporates regulatory requirements and technological innovations. They are intended to provide guidance on market developments, risks, and opportunities.
  The sample report analyzed is two pages long and refers to a single stock.
- Report 4: A pan-European research provider conducts comprehensive equity, ESG, strategy, credit, and quantitative analysis. The teams leverage a multi-local presence to gain company-specific insights and present their findings in structured reports featuring sector ratings, earnings estimates, and valuation methodologies. Quantitative and qualitative elements are combined to identify critical catalysts and risks for investors.
  The sample report analyzed is 25 pages long and covers a single stock.
- Report 5: A West African network of economic and financial experts produces economically sound analyses and offers training programs on financial modeling and data analysis. The reports highlight macroeconomic trends and political factors, place them in a broader economic context, and contain recommendations for economic policy. The reports target both academically interested audiences and aspiring analysts.
  The sample report analyzed is five pages long and refers to a single stock.
- Report 6: A German bank provides economic and market analyses through its research department. Institutional investors can access the reports through a digital portal, which are based on economic models and fundamental market observations. They offer a structured presentation of interest rate and market trends as well as commentary on monetary policy events.
  The sample report analyzed comprises four pages and relates to a single stock.
- Report 7: A German research provider analyzes European and US stocks with a focus on sustainable and transparent companies. The methodology combines fundamental valuation with scientifically validated models and digital tools for detailed company

analysis. Investors receive structured reports with valuation metrics, risk indicators, and strategy recommendations.

The sample report analyzed is five pages long and refers to a single stock.

- Report 8: An Asian bank positions its research unit as a thought leader, combining bottom-up company analysis with macroeconomic themes. Specialized teams examine currencies, interest rates, major economies, regional stock markets and credit instruments. Reports compile the results, highlighting both tactical investment opportunities and long-term trends.

  The sample report analyzed is seven pages long and refers to a single stock.
- Report 9: A student asset management company at a European university manages its portfolios and produces research reports to bridge the gap between academic teaching and capital market practice. The analyses combine quantitative models and qualitative assessments, cover topics ranging from portfolio strategies to macroeconomic developments, and serve to educate the members.

  The sample report analyzed is 12 pages long and refers to a single stock.
- Report 10: An Australian full-service securities service provider with a strong institutional and private client base offers regular fundamental-oriented individual stock analyses that combine qualitative and quantitative elements. The reports contain company-specific financial ratios and valuation methods such as discounted cash flow and multiples, as well as assessments of opportunities, risks, and market-related catalysts.

  The sample report analyzed comprises six pages and refers to a single stock.
- Report 11: A US online platform for investors combines crowd-based investment analysis with editorial quality control; user reports are reviewed by editors and supplemented with community feedback. The platform also offers quantitative ratings that consider key figures such as valuation, growth, profitability, momentum and earnings revisions. The articles cover a wide range of topics, from individual stocks to macroeconomic issues.

  The sample report analyzed is eight pages long and refers to a single stock.

The descriptive analysis applies the criteria to these reports, summarizing scores and weighted aggregates to identify patterns and compare them with the AI-DSS artifact. Results are presented as follows, grouped by each category. For each category and its corresponding criteria, the minimum, maximum, mean, and standard deviation are calculated, excluding

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the AI-DSS Report Score. This exclusion prevents the AI-DSS report score from influencing the peer group's summary statistics. Then, the difference between the AI-DSS score and the mean is determined. This method facilitates comparison and reduces potential bias from outliers associated with the AI-DSS Investment report score. The disclosed individual scores can be found in Appendix 2. The subsequent phase consists of systematically assessing each category and analyzing the aggregate scores for comparison.

Table 7: Results of Framework Analysis: Category Transparency

Category	Criterion	Rating	Weighting (in %)	Score AI-DSS	Minimum (excluded AI-DSS)	Maximum (excluded AI-DSS)	Mean (excluded AI-DSS)	Standard-deviation (excluded AI-DSS)	Difference AI-DSS/MEAN
Transparency	1.1 Clarity and comprehensibility	1 (very unclear) to 5 (very clear)	10	4	2.00	4.00	3.27	0.90	0.73
Transparency	1.2 Disclosure of risks and uncertainties	1 (no disclosure) to 5 (full disclosure)	10	5	1.00	4.00	2.36	1.21	2.64
Transparency	1.3 Comprehensibility of the recommendation	1 (not comprehensible) to 5 (very comprehensible)	10	4	1.00	5.00	2.27	1.42	1.73

Source: own elaboration

The category transparency includes three criteria, where each criterion is assigned a weight of 10%. Reports display variability in this area, with average scores ranging from 2.3 to 3.3. The AI-DSS reveals significant variations in scores, especially in the area of risk disclosure. The variability among reports is moderate to high (standard deviation: 1.4 for Criterion 1.3), reflecting differences in reporting quality; for instance, Report 9 achieved a score of 5 in Criterion 1.3, whereas several others scored only 1. The average rating for the reports across the three criteria is approximately 2.6, while the AI-DSS receives a score of 4.3 (difference: +1.7). The AI-DSS shows higher scores in risk presentation, suggesting more comprehensive handling of uncertainties. Some reports, such as No. 9 or 6, receive high individual scores, although the overall consistency varies.

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Table 8: Results of Framework Analysis: Category Adjustment to risk willingness

Category	Criterion	Rating	Weighting (in %)	Score AI-DSS	Minimum (excluded AI-DSS)	Maximum (excluded AI-DSS)	Mean (excluded AI-DSS)	Standard-deviation (excluded AI-DSS)	Difference AI-DSS/MEAN
Adjustment to risk willingness	2.1 Consideration of risk profiles	1 (no consideration) to 5 (strong consideration)	10	4	1.00	1.00	1.00	0.00	3.00
Adjustment to risk willingness	2.2 Individualized decision support	1 (not individualized) to 5 (highly individualized)	10	4	1.00	1.00	1.00	0.00	3.00
Adjustment to risk willingness	2.3 Flexibility of the analyses	2 (not individualized) to 5 (highly individualized)	10	3	1.00	1.00	1.00	0.00	2.00

Source: own elaboration

This adjustment to risk willingness is determined by three criteria, each assigned a weight of 10%. The reports achieved an average score of 1.0 for all criteria, showing no variance, as all reports received a score of 1. In contrast, the AI-DSS was rated between 3 and 4. The largest observed difference in this category is that the reports do not reflect adaptation to individual risk profiles. The average score for reports is 1.0, whereas the AI-DSS has an average score of 3.7, resulting in a difference of +2.7. This indicates that the reports provide limited flexibility or customization, while the AI-DSS exhibits greater capabilities in these areas. No report showed a positive deviation, suggesting a consistent pattern. Next, the relevance and completeness are evaluated.

Table 9: Results of Framework Analysis: Category Relevance and completeness

Category	Criterion	Rating	Weighting (in %)	Score AI-DSS	Minimum (excluded AI-DSS)	Maximum (excluded AI-DSS)	Mean (excluded AI-DSS)	Standard-deviation (excluded AI-DSS)	Difference AI-DSS/MEAN
Relevance and completeness	3.1 Completeness of the analyses	1 (very incomplete) to 5 (very complete)	10	5	1.00	4.00	2.82	0.98	2.18
Relevance and completeness	3.2 Relevance for investment decisions	1 (not relevant) to 5 (very relevant)	10	5	1.00	4.00	2.55	0.82	2.45
Relevance and completeness	3.3 Integration of different data sources	1 (no integration) to 5 (strong integration)	5	4	2.00	4.00	3.09	0.83	0.91

Source: own elaboration

The analysis covers relevance and completeness, with criteria 3.1 and 3.2 each weighted at 10% and criterion 3.3 weighted at 5%. The average report scores range from 2.5 to 3.1, showing moderate variation; for instance, Report 9 achieves a score of 4 on several criteria, whereas Report 11 scores between 1 and 2. The AI-DSS excels in completeness and relevance (score: 5) but shows less distinction in data integration. The unweighted average is

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2.8 for reports and 4.7 for the AI-DSS - a difference of +1.9. Weightings do not significantly affect this gap.

To summarize, reports are relevant in data integration, but they lack completeness; the AI-DSS provides better-integrated data and more actionable investment analyses.

Table 10: Results of Framework Analysis: Category Efficiency and practicability

Category	Criterion	Rating	Weighting (in %)	Score AI-DSS	Minimum (excluded AI-DSS)	Maximum (excluded AI-DSS)	Mean (excluded AI-DSS)	Standard-deviation (excluded AI-DSS)	Difference AI-DSS/MEAN
Efficiency and practicability	4.1 User-friendliness	1 (not user-friendly) to 5 (very user-friendly)	10	5	2.00	5.00	3.09	1.04	1.91
Efficiency and practicability	4.2 Practical suitability	1 (not suitable for practical use) to 5 (very suitable for practical use)	5	5	1.00	4.00	2.64	1.03	2.36

Source: own elaboration

The final category, efficiency and practicability, consists of two criteria weighted at 10% (4.1) and 5% (4.2). Report scores average 2.85 with considerable variation, while AI-DSS consistently scores 5.0, demonstrating greater user-friendliness and efficiency. Some reports, like 8 and 9, score higher, but overall, the reports are less practical compared to AI-DSS.

The overall ratings of the reports (Table 11) range from 1.25 to 3.30 (average 2.22), while the AI-DSS scores 4.35, outperforming by +2.13. Reports are consistently weak in risk adjustment and vary in transparency and efficiency. Even the best report (No. 9) nearly matches the AI-DSS in relevance but falls short overall. The AI-DSS excels in completeness, customization, and practicality. Report weaknesses include limited flexibility and risk management, with occasional strengths in clarity or relevance. This instance underscores the artifact's effectiveness in minimizing information asymmetries, thereby lending stronger support to the hypothesis.

Table 11: Results of Framework Analysis: Overall Ratings

Category	Criterion	Rating	Weighting (in %)	Score AI-DSS	Minimum (excluded AI-DSS)	Maximum (excluded AI-DSS)	Mean (excluded AI-DSS)	Standard-deviation (excluded AI-DSS)	Difference AI-DSS/MEAN
Overall Score			100,00	4.35	1.25	3.30	2.22	0.61	2.13

Source: own elaboration

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5.2.3 Quantitative Questionnaire

The second part of the evaluation uses a quantitative questionnaire to test the research hypothesis. The AI-DSS output is provided to a group of experts, who then complete the questionnaire based on their assessment of the artifact.

This expert feedback can support a hypothesis even with a limited number of experts (Lakens, 2022). Studies indicate that a small, homogeneous group of experts can provide empirically reliable evaluations, as their aligned knowledge ensures effective and trustworthy results (Akins et al., 2005).

A study demonstrates that questionnaire data can undergo double bootstrapping to assess the robustness of the findings. Consequently, the data analysis comprises three stages. Initially, the observed metrics are examined. Subsequently, two bootstrapped datasets are generated through computational methods - one utilizing 1,000 resampling iterations and the other 2,000. Third, these three datasets are compared by evaluating their means, trimmed means and standard deviations within a 95% confidence interval (CI). To ensure the transparency of the thesis, the trimmed means and additional statistical indicators are presented in Appendix III. The study indicates that when the confidence intervals and metrics of the computed datasets are comparable to those observed, a high degree of stability is demonstrated (Akins et al., 2005). Another study demonstrates a clear distinction between quantitative and qualitative sample sizes and introduces a concept for determining the ideal sample size. The study proposes the concept of "information power," which suggests that the more relevant information contained within a study, the fewer participants are needed (Malterud et al., 2016).

These studies indicate that incorporating expert validation, bootstrap procedures, and metric comparisons is relevant in the design and evaluation of questionnaires, particularly when working with small sample sizes. The next section defines experts and the scoring logic and provides an outline of the questionnaire along with a descriptive analysis of the responses.

5.2.3.1 Definition and Selection of Experts

There is currently no universally agreed-upon definition of an expert within the scientific community. Accordingly, it is essential to define clear criteria for determining expertise within each research context (Krell & Lamnek, 2024). Experts are typically recognized as individuals with technical, procedural, and interpretive knowledge relevant to their specific professional domains. Professional expertise is distinguished by its foundation on multiple

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layers of knowledge, integrating not only theoretical understanding but also practical experience and specialized interpretative abilities (Bogner et al., 2002; Gläser & Laudel, 2010). Practice contexts and the demands of respective work environments intrinsically connect to the development and refinement of this knowledge. Consequently, experts possess the capacity to exert considerable influence over decision-making processes and workflow design within their areas of responsibility, leveraging both personal and collective knowledge. This unique role enables them to significantly shape organizational routines and perspectives among peers (Bogner et al., 2002). In summary, expertise in a particular field should not be considered a personal resource; rather, it is an attribution made by researchers based on specific epistemic interests (Bogner et al., 2002).

For this research, experts are characterized as individuals with professional experience in the financial services sector. The analysis is structured in two phases: first, the researcher evaluates and scores prospective experts. Second, these assessments are cross-validated using responses from the introduction section of the quantitative questionnaire; see 5.2.3.2 (Krogh & Vedelsby, 1994).

A matrix is constructed to evaluate candidates using a scoring system derived from publicly available information, covering a cohort of 15 to 20 proven experts. This approach aligns with multiple criteria decision-making methodologies or can be viewed as a multi-attribute utility technique, as the selection process is based on multiple criteria and involves aggregating values relevant to each attribute for an overall assessment of each alternative (Henderson, 2015; Jansen, 2011). Expert status is determined by the researcher through a review of materials such as curricula vitae and professional profiles on platforms like LinkedIn. This methodology facilitates objective analysis of each individual’s qualifications regarding the evaluation of the AI-DD artifact - the investment report - by leveraging transparent, accessible data.

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Table 12: Initial Evaluation of Experts

Criterion	Options and Scoring	Reasons for integration into initial scoring
Professional experience in the financial market context	Less than 2 years: 0 2-5 years: 1 6-10 years: 2 More than 10 years: 3	Estimate based on CV/LinkedIn (e.g., job history). This allows comparison with self-assessment to identify overestimations/underestimations.
Knowledge in business administration and finance from formal or informal education	No, no relevant knowledge: 0 Yes, basic knowledge (e.g., through individual courses, certificates, seminars): 1 Yes, in-depth knowledge (e.g., through studies or intensive further training): 2	Records participants' prior knowledge of economics gained through school, university, or non-university education. Serves to classify the economic background in order to better interpret the assessment competence and expectations regarding the analyzed report.
Frequency of working with analyst reports	Never: 0 Occasionally: 1 Regularly: 2 Frequently: 3	Estimation based on publications or roles (e.g., "Daily Analyst" → 3). Integrates self-assessment, as it measures routine.
Familiarity with analysis (e.g., stocks, ESG, fundamental data)	None: 0 Basic knowledge: 1 Advanced: 2 Expert level: 3	Based on certificates/publications (e.g., ESG reports → 3). Central to self-assessment, as it queries competence levels.
Frequency of investment decisions	Never: 0 Occasionally: 1 Regularly: 2 Frequently: 3	From areas of responsibility (e.g., "investment manager" → 3). Records practical application of self-assessment.
Financial background (qualitative)	No scoring, but bonus/penalty (±1–2)	Briefly evaluate the note (e.g., "ESG specialist"). Compare with the actual description to check consistency.

Source: own elaboration

Subsequently, selected experts receive access to both the quantitative questionnaire and the AI-DSS artifact. The researcher combines the responses to the introduction section of the quantitative questionnaire with preliminary scoring. This selection process aims to reduce bias by ensuring that only individuals with demonstrable expertise provide input, thereby minimizing the risk of collecting data based on insufficient knowledge (Lakens, 2022).

5.2.3.2 Blueprint of the Quantitative Questionnaire

The quantitative questionnaire, provided with the AI-DSS artifact document, is administered via an online questionnaire tool. Experts are informed that they have to read the AI-DSS artifact before beginning the questionnaire. The questionnaire is divided into six sections. The first section is an introduction, which outlines the research objectives and explains the methodological background for this type of evaluation. It also includes information regarding data privacy and license agreements.

The second section focuses on self-assessment of the respondent's expertise. As previously noted, the researcher validates the experts using specific criteria, and these criteria are cross-validated in this section. Since these criteria have already been described in the earlier part, they will not be repeated in this section; instead, the emphasis will be on subsequent sections of the questionnaire.

Following the introduction, the report's elements are evaluated using a Likert scale with targeted statements regarding their completeness, clarity and relevance. Respondents rate each statement from 1 (strongly disagree) to 5 (strongly agree). These deductively selected statements relate to the hypotheses and the AI-DSS framework, covering all areas of the investment report as mentioned in 5.1 (see Table 13).

Table 13: Quantitative rating of aspects like completeness, clarity and relevance

Statement	Section of the AI-DSS report	Eval Phase
The AI-DSS report provides a comprehensive and transparent overview of Mercedes-Benz Group AG (e.g., market position, financial data, ESG performance).	Management Summary, Company Description	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The stock price analysis (e.g., trend analysis, volatility, risk assessment) in the AI-DSS report is clearly presented and supports investors with a risk-neutral risk profile in their decision-making.	Technical Analysis	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The fundamental data (e.g., profitability, stability, sales trends) in the AI-DSS report is well structured and facilitates the assessment of the company's financial health from the perspective of a risk-neutral investor.	Fundamental Analysis	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.

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Statement	Section of the AI-DSS report	Eval Phase
The analysis of the shareholder structure (e.g., institutional ownership, free float) in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions from the perspective of a risk-neutral investor.	Shareholder Structure Assessment	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The ESG rating (environmental, social, governance) in the AI-DSS report is understandable and relevant for investors who consider sustainability.	ESG-Analysis	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The analysis of sentiment and analyst ratings in the AI-DSS report is relevant and presented in a comprehensible manner, facilitating investment decisions.	Sentiment Analysis and Analysts Ratings	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The risk analysis in the AI-DSS report is relevant and presented in a comprehensible manner, facilitating the assessment of the company's risk profile.	Risk Analysis	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The overall risk analysis in the AI-DSS report provides a comprehensive overview of the assessment of individual report components and facilitates understanding of the risk classification.	Overall Risk Assessment	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.

Source: own elaboration

Following the Likert scale questions, this section concludes with an open-ended item designed to gather qualitative feedback on the strengths and weaknesses of the report's content, particularly regarding its relevance and comprehensibility for investors. By combining these two question formats, the evaluation aims to support both the research hypothesis and offer qualitative advice for future studies.

The following section, along with the previous one, presents Likert scale statements for expert evaluation. These statements address reducing information asymmetries through the AI-DSS artifact (see

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Table 14).

Table 14: Quantitative rating of Reducing Information Asymmetries

Statement	Eval Phase
The AI-DSS report provides a comprehensive and transparent overview of Mercedes-Benz Group AG (e.g., market position, financial data, ESG performance).	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The report increases transparency regarding the financial position, risks and market position of Mercedes-Benz Group AG, thereby reducing information asymmetries.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The report provides tailored information that helps investors make informed decisions based on their risk willingness.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The combination of different analyses (e.g., stock price, ESG, fundamental data) provides a comprehensive picture that effectively eliminates information asymmetries.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The report adequately addresses potential uncertainties (e.g., declines in profitability, market volatility) to strengthen investor confidence.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.

Source: own elaboration

As in the previous section, the Likert questionnaires are followed by an open-ended item intended to collect qualitative feedback regarding the main challenges in reducing information asymmetries in stock analyses, for example, limited data availability, complex presentation, or trust in automated analysis.

The following section examines the efficiency and practical applicability of the AI-DSS artifact. It compares the report's efficiency with that of professional analyses, evaluates its applicability, and seeks recommendations for supporting AI-DSS objectives. To assess efficiency, respondents are asked to indicate the typical time required to produce a comparable stock analysis, choosing from options such as less than 2 hours, 2 to 4 hours, 4 to 8 hours, and more than 8 hours. Additionally, a Likert scale questionnaire is administered based on the statements in Table 15, followed by two open-ended questions regarding potential improvements to enhance the efficiency, transparency, and usability of the report, as well as suggestions for optimizing the report to address information asymmetries.

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Table 15: Quantitative rating of efficiency and practical usability

Statement	Eval Phase
Compared to manual analysis, the AI-DSS report saves time without compromising transparency or quality.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The report is efficient and enables faster decision-making for investors.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The report is useful and practical for investors in practice (e.g., portfolio management, investment decisions).	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.
The recommended course of action for risk-neutral investors is understandable and justified by the analyses, which improves the quality of decision-making.	Eval 3 and Eval 4 to validate the user-friendliness, robustness, effectiveness and practical suitability of the artifact.

Source: own elaboration

The questionnaire concludes with a section expressing gratitude to participants. Through these sections, the AI-DSS will be evaluated by selected experts based on the stated hypotheses. The questionnaire primarily utilizes quantitative measures via Likert scale questions. To obtain more profound insights and require future research directions, it also incorporates open-ended items to gather qualitative feedback.

5.2.3.3 Descriptive Analysis of the given Answers and Results

The quantitative evaluation of the AI-DSS artifact was conducted using responses from 18 validated experts in the financial services sector. As outlined in the methodological framework (see Section 5.2.3.1 for expert selection and Section 5.2.3.2 for the questionnaire blueprint), the analysis employed a combination of descriptive statistics, robust estimators, and bootstrap resampling techniques to ensure reliable inferences despite the small sample size (N=18). Specifically, bootstrap methods were applied to compute confidence intervals for means, trimmed means (10% trimming) and reliability measures.

Two bootstrap approaches were used:

1. the percentile bootstrap, which derives confidence intervals (short: CIs) from the quantiles of the bootstrap distribution (e.g., 2.5th and 97.5th percentiles for 95% CIs), and
2. the bias-corrected and accelerated (bca) bootstrap, which adjusts for bias and skewness using jackknife estimators for improved accuracy in small or skewed samples. Resampling was performed at the person level with replacement (B=1000 and B=2000 iterations) to preserve within-person response structures, particularly for multivariate metrics like Cronbach's alpha (Akins et al., 2005; Cronbach, 1951; Kim & Yeasmin, 2005; Wilcox, 2003).

This resampling strategy ensures that the bootstrap distributions reflect the original data's variability while accounting for potential ties in Likert-scale responses. Additionally, robust statistics such as medians and median absolute deviations (MAD, both raw and scaled by 1.4826 for normality approximation) were calculated, though not directly reported here for brevity (Mosteller & Tukey, 2020). Reliability was assessed via classical Cronbach's alpha (with bootstrap CIs), alpha-if-item-deleted, corrected item-total correlations (CITC, using Pearson and polychoric methods (Olsson, 1979; Pearson, 1896)), with flags for values < 0.30) and ordinal measures (alpha and omega based on polychoric correlations for Likert data). Deviations between observed values and bootstrap means (obs - boot) were computed to assess stability, and CI overlaps between B=1,000 and B=2,000 were evaluated (100% overlap across all items and methods indicating high stability, see Table 16). Relative CI widths (CI width divided by the scale range of 4.0 for Likert 1-5) were low (0.149-0.188), suggesting precise estimates. In psychometric analyses of Likert scales, relative confidence interval widths below 0.20 indicate high estimation precision, which is attributable to sufficient sample size and low data variability and supports the generalizability of the results to the target population (Cumming & Finch, 2005). All analyses were generated using R-based tools for bootstrap and psychometric computations. To provide an overview of the bootstrap stability across sections, the following summary table highlights key metrics per scale and method (Table 16).

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Table 16: Bootstrap Stability Metrics for Likert-Scale Evaluations

Table	Method	Items	CI overlap 1k↔2k	rel. CI width (1k)	rel. CI width (2k)
Evaluation of report content (Likert scale)	percentile	8	100.0%	0.158	0.160
Evaluation of report content (Likert scale)	bca	8	100.0%	0.158	0.162
Evaluation of the reduction of information asymmetries (Likert scale)	percentile	4	100.0%	0.149	0.156
Evaluation of the reduction of information asymmetries (Likert scale)	bca	4	100.0%	0.154	0.156
Time expenditure and efficiency assessments (Likert scale)	percentile	4	100.0%	0.177	0.184
Time expenditure and efficiency assessments (Likert scale)	bca	4	100.0%	0.188	0.185

Source: own elaboration

The table depicts that all confidence intervals nearly match and are very narrow. This evidence shows the bootstrap method is reliable: different approaches yield a similar result, and outliers or sampling do not distort the findings (Akins et al., 2005).

5.2.3.4 Demographic Profiles of Respondents

The expert panel comprised n=18 participants with a well-balanced distribution of professional experience: While only one participant had less than two years of experience, seven experts each possessed either 2–5 years or more than 10 years of professional experience, and three participants had 6–10 years. All respondents demonstrated comprehensive knowledge in business administration and finance, acquired through formal or informal education.

Regarding the practical application of this knowledge, the panel showed varying levels of engagement with analyst reports: Half of the experts (n=9) used them only occasionally (less than monthly), while n=4 consulted them regularly on a monthly basis and n=5 frequently accessed them weekly or more often. Specific analytical expertise in stock, ESG, and fundamental analysis was evenly distributed: n=7 each classified themselves at basic and advanced levels, respectively, while n=4 claimed expert status.

These theoretical and analytical capabilities were reflected in practical investment activities: While only one expert was never involved in investment decisions, n=8 occasionally made or advised on such decisions, n=4 did so regularly, and n=5 were frequently engaged in investment decision-making processes.

These profiles validate the panel’s qualifications and align with the multi-criteria scoring system adopted during selection. Subsequently, each section of the questionnaire will be analyzed using the established methodology and evaluated accordingly.

5.2.3.5 Evaluation of Report Content (8 Items)

This section represents a key highlight of the evaluation. It assesses the completeness, clarity and relevance of the AI-DSS report's components using a 5-point Likert scale (1 = totally disagree, 5 = totally agree). The observed means ranged from 3.83 to 4.33, indicating generally positive evaluations (see also Table 17). All values were above the neutral midpoint of 3.0. The highest-rated item was the shareholder structure analysis (Mean=4.33, 95% CI [3.98, 4.69]). This component was praised for its relevance and understanding in supporting risk-neutral investment decisions. In contrast, the stock price analysis received the lowest rating (M=3.83, 95% CI [3.47, 4.20]), though this evaluation remained favorable. The bootstrap CIs (percentile and bca) showed similar results across B=1,000 and B=2,000. The mean |obs - boot| deviations were 0.004 (B=1,000) and 0.003 (B=2,000), confirming the robustness of the analysis. For instance, the comprehensive overview item's percentile CI (B=2,000) was [3.78, 4.56]. This closely matches the bca CI [3.67, 4.44]. The trimmed means (removing 10% extremes) were slightly higher, ranging from 3.88 to 4.44. These showed comparable CIs, suggesting minimal outlier influence on the results (cf. Table 17 and Figure 19).

To provide a detailed overview of the individual evaluation criteria, the following table presents the observed means along with the corresponding bootstrap confidence intervals for each item. This ensures transparency regarding the statistical robustness of the results.

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Table 17: Item-Level Means and Bootstrap Confidence Intervals for Report Content Evaluation

Item:	n	Mean (obs)	95% CI (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs(obs−boot) [1k]	abs(obs−boot) [2k]
The AI-DSS report provides a comprehensive and transparent overview of Mercedes-Benz Group AG (e.g., market position, financial data, ESG performance).	18	4.17	[3.77, 4.56]	[3.72, 4.56]	[3.78, 4.56]	[3.61, 4.44]	[3.67, 4.44]	0.007	0.004
The ESG (environmental, social, governance) assessment in the AI-DSS report is understandable and relevant for investors who consider sustainability.	18	4.17	[3.80, 4.53]	[3.78, 4.50]	[3.78, 4.50]	[3.72, 4.44]	[3.72, 4.44]	0.000	0.004
The analysis of sentiment and analyst ratings in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions.	18	4.17	[3.93, 4.40]	[3.94, 4.39]	[3.94, 4.39]	[3.89, 4.33]	[3.89, 4.33]	0.003	0.004
The analysis of the shareholder structure (e.g., institutional ownership, free float) in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions from the perspective of a risk-neutral investor.	18	4.33	[3.98, 4.69]	[3.94, 4.67]	[3.94, 4.67]	[3.82, 4.56]	[3.83, 4.57]	0.001	0.005
The fundamental data (e.g., profitability, stability, forecasts) in the AI-DSS report is well structured and facilitates the assessment of the company's financial health from the perspective of a risk-neutral investor.	18	4.28	[4.01, 4.54]	[4.06, 4.56]	[4.00, 4.56]	[3.97, 4.46]	[3.94, 4.50]	0.007	0.001
The overall risk analysis in the AI-DSS report provides a comprehensive overview of the assessment of individual report components and facilitates understanding of the risk classification.	18	4.00	[3.78, 4.22]	[3.78, 4.22]	[3.78, 4.22]	[3.78, 4.17]	[3.72, 4.17]	0.002	0.002
The risk analysis in the AI-DSS report is relevant and presented in a comprehensible manner, facilitating the assessment of the companys risk situation.	18	3.94	[3.54, 4.35]	[3.56, 4.28]	[3.56, 4.33]	[3.50, 4.22]	[3.50, 4.28]	0.010	0.003
The stock price analysis (e.g., trend analysis, volatility, risk assessment) in the AI-DSS report is clearly presented and supports investors with a risk-neutral risk profile in their decision-making.	18	3.83	[3.47, 4.20]	[3.50, 4.17]	[3.50, 4.17]	[3.39, 4.11]	[3.39, 4.11]	0.002	0.004

Source: own elaboration

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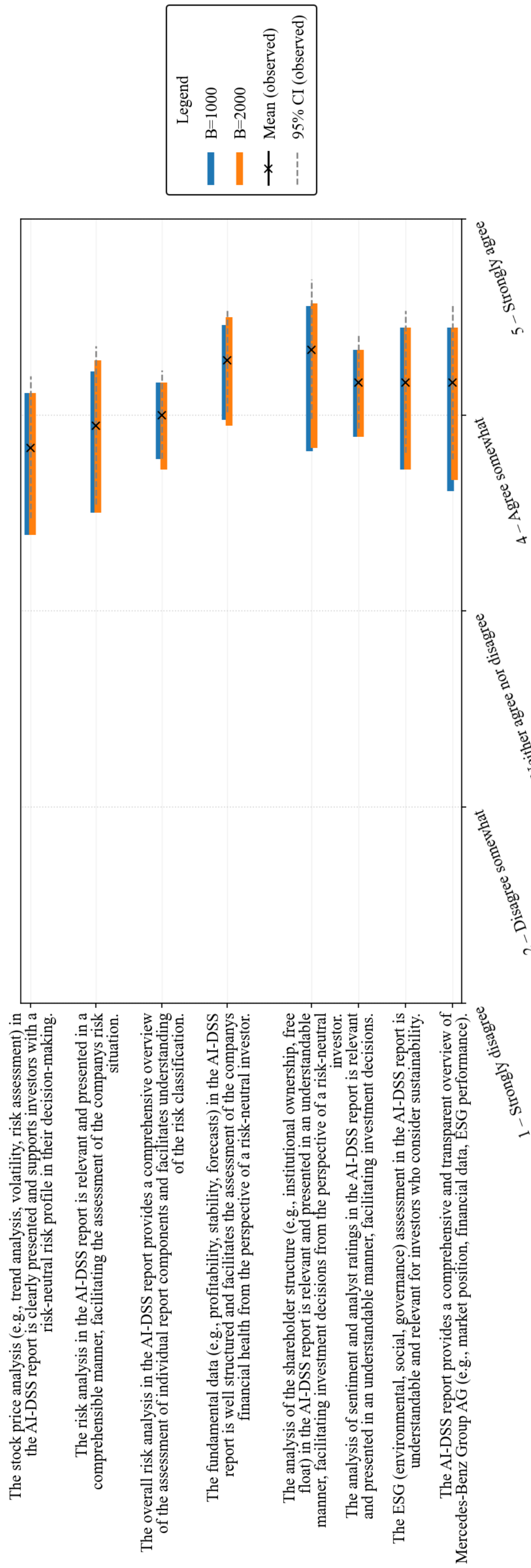

Figure 19: Bootstrap confidence intervals by item - bca (B=1,000 vs. B=2,000)

Source: own elaboration

The reliability analysis demonstrated the scale's strong internal consistency. The observed Cronbach's alpha was 0.837, with 95% confidence intervals of [0.583, 0.919] for B=1,000 and [0.607, 0.921] for B=2,000. The alpha-if-item-deleted values ranged from 0.798 to 0.837. All values were equal to or lower than the overall alpha, indicating that no individual item reduced the scale's consistency. This finding supports the homogeneity of the scale.

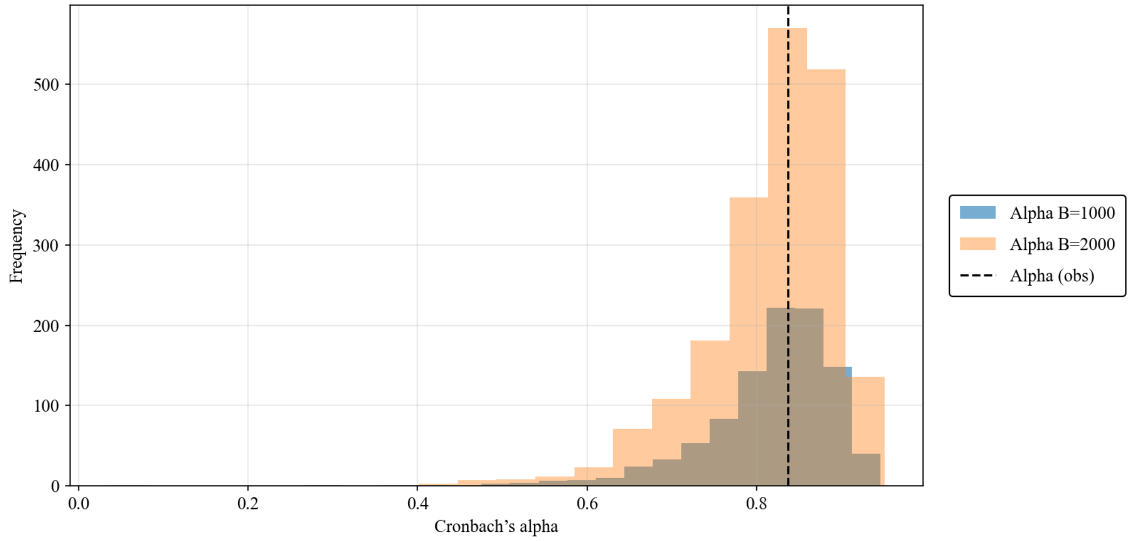

Figure 20: Distribution of Cronbach's alpha (bootstrap; B=1,000/2,000)

Source: own elaboration

The corrected item-total correlation (CITC) values further confirmed outstanding item discrimination. Pearson correlations ranged from 0.396 to 0.787, while polychoric correlations ranged from 0.499 to 0.971. When treating Likert scale data as ordinal, which is appropriate due to their ordered categorical nature, reliability measures such as ordinal alpha and omega based on polychoric correlations were higher than those based on metric assumptions (Gadermann et al., 2021). Both Cronbach's alpha and McDonald's omega reached 0.915, indicating optimal internal consistency. The following section will examine the reduction of information asymmetries.

5.2.3.6 Evaluation of Reducing Information Asymmetries (4 Items)

This section represents another central highlight of the evaluation. It assessed the AI-DSS report's effectiveness in minimizing information asymmetries through transparency and comprehensive analysis, using the same 5-point Likert scale. The observed means ranged from 3.72 to 4.39, reflecting overall positive perceptions; see also Table 18. All values were above the neutral midpoint, indicating favorable evaluations across all items. The highest-

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rated item was the increase in transparency regarding financial situation, risks, and market position (M=4.39, 95% CI [4.07, 4.71]). This result highlights the report's significant role in reducing information asymmetries. In contrast, the provision of tailored information based on risk willingness received the lowest rating (M=3.72, 95% CI [3.37, 4.07]). This finding indicates room for improvement in the personalization aspect of the system. The bootstrap confidence intervals demonstrated high stability across different bootstrap samples. There was 100% overlap between the B=1,000 and B=2,000 results. The mean |obs - boot| values were 0.006 for B=1,000 and 0.002 for B=2,000, confirming the robustness of the estimates. For example, the comprehensive picture item's percentile CI (B=2,000) was [4.00, 4.56], while the bca CI was [4.00, 4.50]. The trimmed means ranged from 3.75 to 4.44 and their corresponding confidence intervals remained consistent. This phenomenon demonstrates the resilience of the results to potential outliers; see also Table 18 and Figure 21.

Table 18: Item-Level Means and Bootstrap Confidence Intervals for Reducing Information Asymmetries

Item	n	Mean (obs)	95% CI (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs(obs−boot) [1k]	abs(obs−boot) [2k]
The combination of various analyses (e.g., share price, ESG, fundamental data) provides a comprehensive picture that effectively eliminates information asymmetries.	18	4.28	[4.01, 4.54]	[4.05, 4.50]	[4.00, 4.56]	[4.00, 4.44]	[4.00, 4.50]	0.008	0.003
The report adequately addresses potential uncertainties (e.g., declines in profitability, market volatility) to strengthen investor confidence.	18	3.83	[3.47, 4.20]	[3.50, 4.17]	[3.50, 4.17]	[3.38, 4.11]	[3.39, 4.11]	0.008	0.003
The report increases transparency regarding the financial situation, risks and market position of Mercedes-Benz Group AG, thereby reducing information asymmetries.	18	4.39	[4.07, 4.71]	[4.06, 4.67]	[4.06, 4.67]	[4.00, 4.61]	[4.00, 4.61]	0.000	0.002
The report provides tailored information that helps investors make informed decisions based on their risk willingness.	18	3.72	[3.37, 4.07]	[3.39, 4.06]	[3.39, 4.06]	[3.33, 4.00]	[3.33, 4.00]	0.010	0.001

Source: own elaboration

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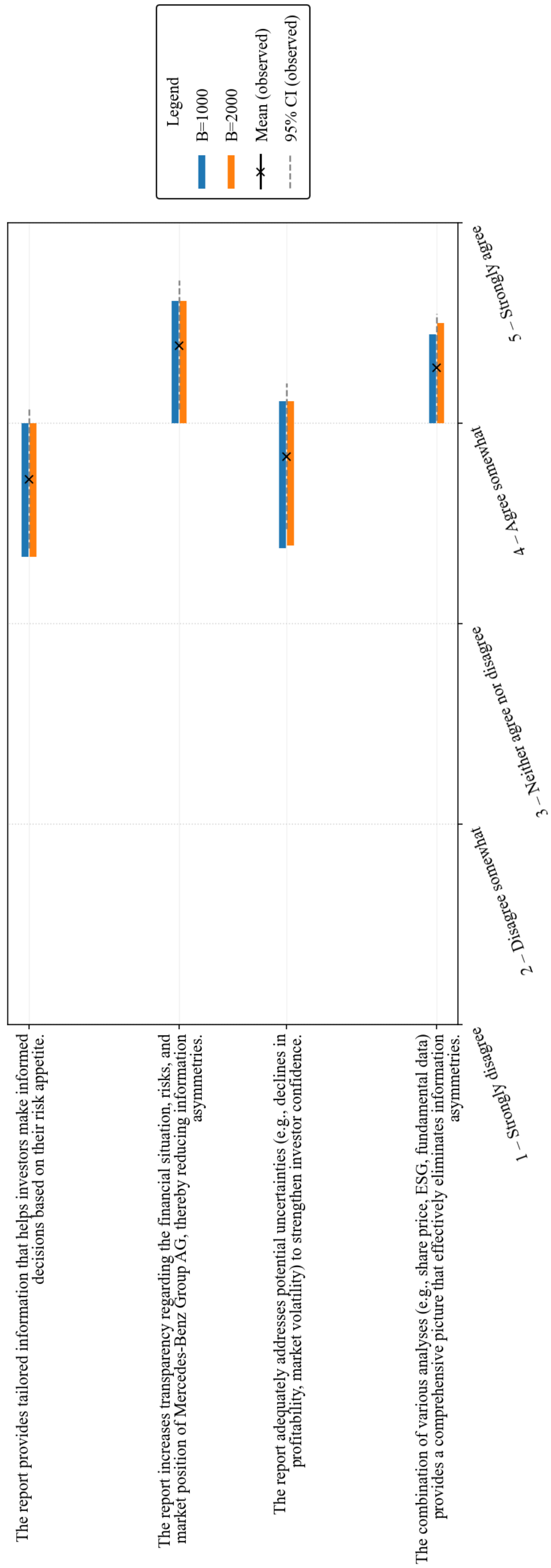

Figure 21: Bootstrap confidence intervals by item - BCa (B=1000 vs. B=2000)

Source: own elaboration

The reliability analysis revealed acceptable internal consistency for this scale. The observed Cronbach's alpha was 0.760, with 95% confidence intervals of [0.552, 0.853] for B=1,000 and [0.548, 0.851] for B=2,000 (Figure 20). The alpha-if-item-deleted values ranged from 0.666 to 0.746. All values were equal to or lower than the overall alpha, indicating that no individual item reduced the scale's consistency. This suggests that the scale demonstrates homogeneity.

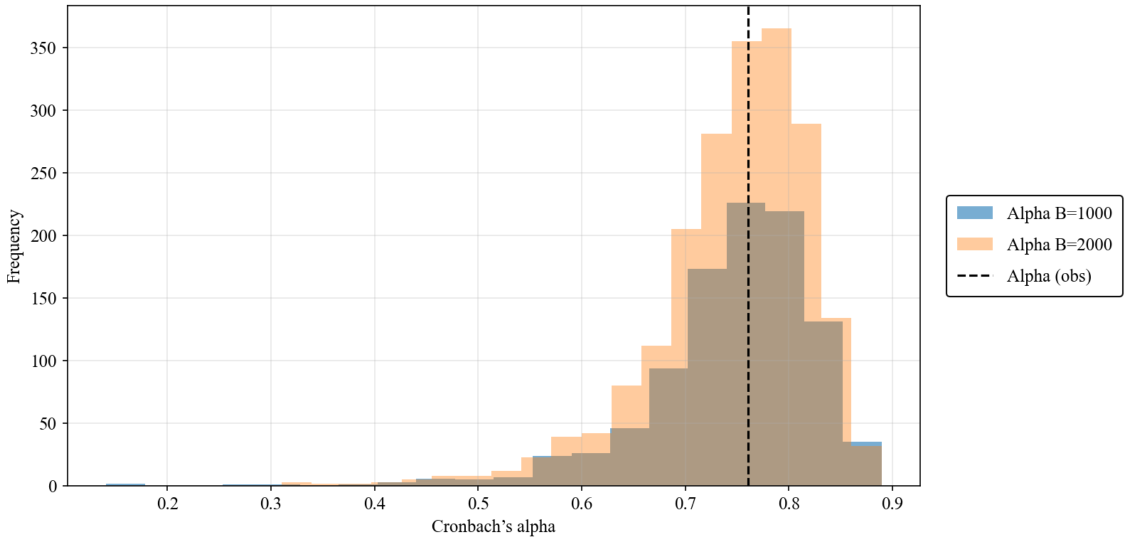

Figure 22: Distribution of Cronbach's alpha (bootstrap; B=1,000/2,000)

Source: own elaboration

The corrected item-total correlation (CITC) values supported adequate item discrimination. Pearson correlations ranged from 0.486 to 0.625, while polychoric correlations ranged from 0.532 to 0.775. All values exceeded the minimum threshold of 0.30, with no problematic items identified. When treating the data as ordinal, the reliability measures were notably higher and more appropriate for the ordinal nature of Likert scale data. Cronbach's alpha reached 0.838, while McDonald's omega was 0.845, indicating good internal consistency. Next, efficiency and practical usability will be evaluated.

5.2.3.7 Evaluation of Efficiency and Practical Usability (4 Items)

This section evaluated the report's efficiency, time savings and practical utility using the same 5-point Likert scale. The observed means ranged from 3.94 to 4.17, indicating positive evaluations overall across all utility dimensions. The highest-rated aspect was the report's efficiency in enabling faster decision-making processes (M=4.17, 95% CI [3.88, 4.45]), see Table 19. This finding demonstrates that users perceived significant value in the system's ability to accelerate their decision-making workflow. In contrast, the time savings compared to manual analysis received the lowest rating (M=3.94, 95% CI [3.46, 4.43]), though this evaluation remained favorable. The bootstrap confidence intervals demonstrated high statistical stability across different bootstrap samples. There was 100% overlap between the B=1,000 and B=2,000 results. The mean |obs - boot| values were 0.004 for B=1,000 and 0.002 for B=2,000, confirming the robustness of the estimates (see also Table 19 and Figure 23). For example, the practical usability item's percentile CI (B=2,000) was [3.61, 4.39], while the bca CI was [3.50, 4.28]. The trimmed means ranged from 4.00 to 4.19 and their corresponding confidence intervals remained consistent. This indicates strong resilience of the results to potential extreme values.

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Table 19: Item-Level Means and Bootstrap Confidence Intervals for Efficiency and Practical Usability

Item	n	Mean (obs)	95% CI (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs(obs−boot) [1k]	abs(obs−boot) [2k]
The AI-DSS report saves time compared to a manual analysis without compromising transparency or quality.	18	3.94	[3.46, 4.43]	[3.50, 4.39]	[3.44, 4.39]	[3.35, 4.33]	[3.33, 4.28]	0.001	0.002
The recommended course of action for risk-neutral investors is comprehensible and justified by the analyses, which improves the quality of decision-making.	18	4.00	[3.65, 4.35]	[3.67, 4.33]	[3.67, 4.33]	[3.56, 4.22]	[3.56, 4.24]	0.003	0.000
The report is efficient and enables faster decision-making for investors.	18	4.17	[3.88, 4.45]	[3.89, 4.44]	[3.89, 4.44]	[3.82, 4.33]	[3.83, 4.39]	0.010	0.005
The report is useful and practical for investors in practice (e.g., portfolio management, investment decisions).	18	4.00	[3.61, 4.39]	[3.61, 4.33]	[3.61, 4.39]	[3.44, 4.28]	[3.50, 4.28]	0.003	0.002

Source: own elaboration

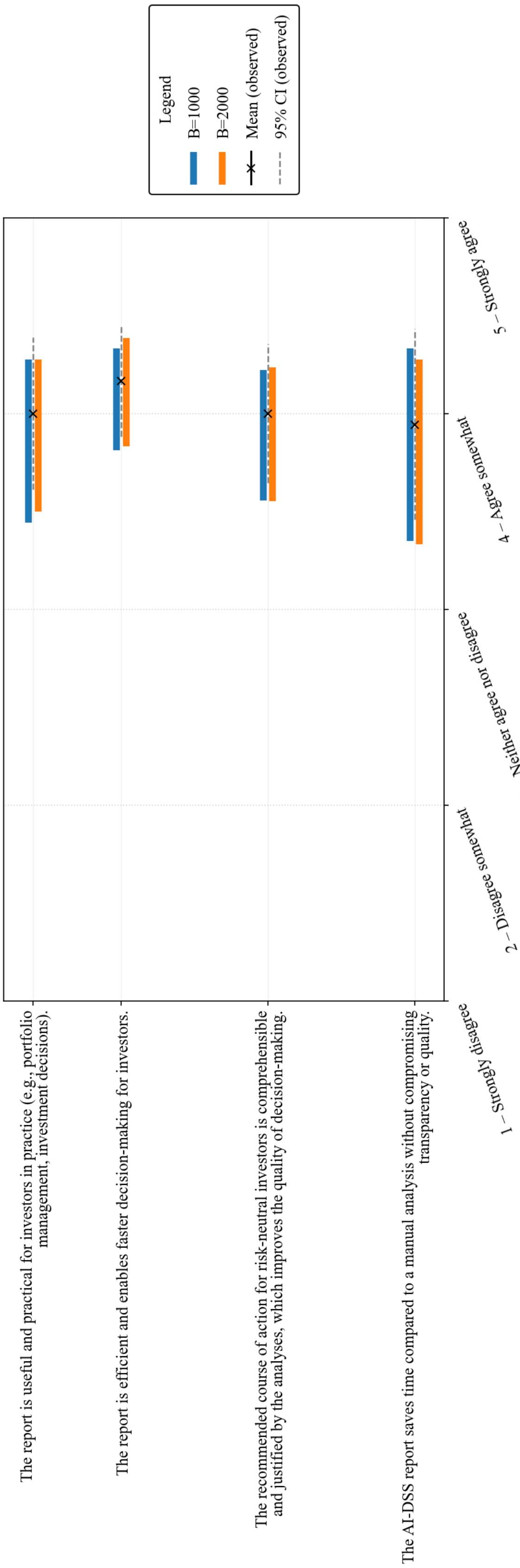

Figure 23: Bootstrap confidence intervals by item - BCa (B=1,000 vs. B=2,000)

Source: own elaboration

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The reliability analysis demonstrated acceptable internal consistency for this scale. The observed Cronbach's alpha was 0.767, with 95% confidence intervals of [0.335, 0.903] for B=1,000 and [0.319, 0.901] for B=2,000 (Figure 24). The wider confidence intervals reflect the smaller item set (k=4), which typically results in less precise estimates. The alpha-if-item-deleted analysis suggested potential areas for scale refinement. Two items showed values slightly higher than the overall alpha: time savings (0.769 > 0.767) and efficiency (0.777 > 0.767). This indicates that removing either of these items would marginally improve the scale's internal consistency, though the differences are minimal and may not warrant revision.

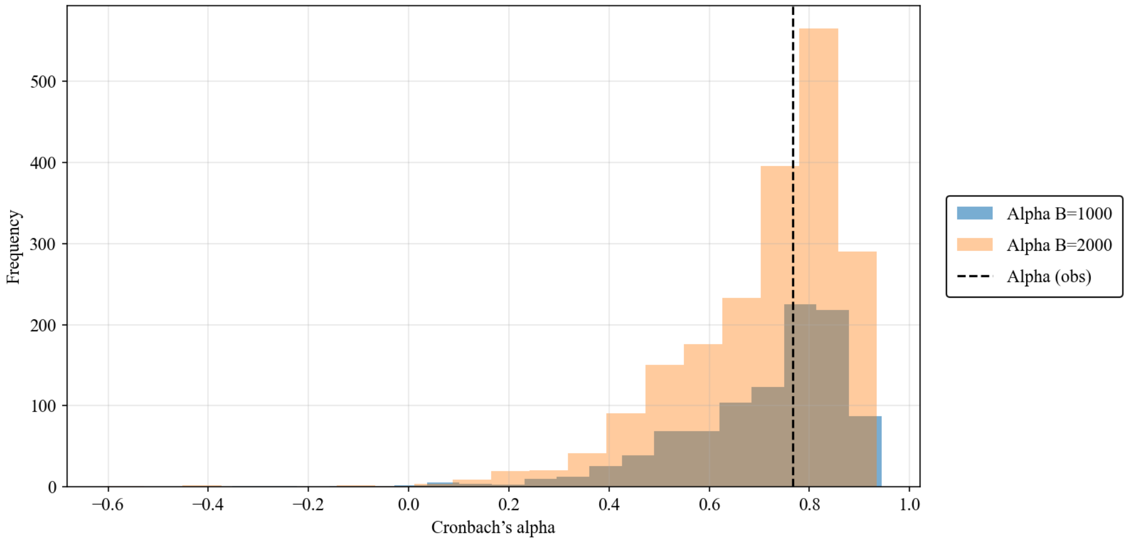

Figure 24: Distribution of Cronbach's alpha (bootstrap; B=1,000/2,000)

Source: own elaboration

The corrected item-total correlation (CITC) values confirmed adequate item discrimination across all items. Pearson correlations ranged from 0.433 to 0.805, while polychoric correlations ranged from 0.528 to 0.935. All values exceeded the minimum threshold of 0.30, with no problematic items identified. When treating the data as ordinal, which is more appropriate for Likert scale data, the reliability measures were notably higher. Ordinal Cronbach's alpha reached 0.823, while McDonald's omega was 0.837. These values indicate excellent internal consistency and reinforce the suitability of ordinal treatment for this type of data.

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In summary, the quantitative evaluation provides strong support for the research hypothesis that AI-based DSS reduce information asymmetries through targeted data analysis. The expert ratings across all three evaluation dimensions were consistently favorable, demonstrating the system's effectiveness in achieving this goal.

Content quality achieved the highest overall rating with a mean across items of approximately 4.11, indicating that the AI-DSS successfully performs targeted data analysis. Most importantly, the reduction of information asymmetries received a mean rating of approximately 4.05, directly supporting the core hypothesis. The efficiency and utility dimension scored approximately 4.03, confirming the practical relevance and trust-building potential of the system. The robust bootstrap estimates validate these findings despite the relatively small expert panel size of N=18. The high confidence interval overlaps, and low deviation values underscore the stability of the estimates, demonstrating that the results are statistically reliable. The reliability metrics further support the internal consistency of all measurement scales used in the evaluation. This psychometric validation strengthens confidence in the substantive findings regarding information asymmetry reduction.

These results provide empirical evidence underpinning the hypothesis that AI-based DSS minimize the discrepancy between information holders and users through targeted analysis, enhanced transparency, and trust-building mechanisms. The positive expert assessments establish a solid foundation for the theoretical framework and inform future refinements of the AI-DSS artifact.

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6 DISCUSSION OF THE RESULTS

This chapter discusses the results from the evaluation of the AI-DSS artifact, integrating findings from the methodological triangulation approach. The discussion synthesizes the framework analysis and expert questionnaire to address the research question - how the AI-DSS supports risk-based investment decisions while reducing information asymmetries - and to test the hypothesis that the system promotes well-founded decisions through targeted data analysis. By linking these results to the DSR framework (Eval 3 and Eval 4), the artifact's usability, robustness, effectiveness and practicality are interpreted. The discussion is structured as follows: a summary of key findings from each evaluation component, an integration of results with theoretical implications, and a reflection on the DSR approach.

6.1 Summary of Framework Analysis Findings

The framework analysis compared the AI-DSS-generated investment report on Mercedes-Benz Group AG with 11 anonymized professional analyst reports, using deductively derived criteria across four categories: transparency, adjustment to risk willingness, relevance and completeness and efficiency, and practicability. Overall, the AI-DSS outperformed the benchmark reports with a weighted aggregate score of 4.35 compared to an average of 2.22 (difference: +2.13), demonstrating superior quality in addressing information asymmetries.

In the transparency category, the AI-DSS scored 4.3 on average, exceeding the reports' mean of 2.6 by 1.7 points. This was particularly evident in the disclosure of risks and uncertainties, where the AI-DSS achieved a perfect score of 5.0 while traditional reports averaged only 2.3. The system demonstrated its superior ability to enhance investor confidence through a clear presentation of analyses covering ESG factors and fundamentals. Traditional reports show variability (with a standard deviation of up to 1.4 for comprehensibility of recommendations), indicating inconsistent quality in conventional reporting practices, while the AI-DSS provided consistent clarity and comprehensibility across all transparency criteria.

The adjustment to the risk willingness category revealed the most substantial contrast, with the AI-DSS averaging 3.7 against a uniform 1.0 for all traditional reports (difference: +2.7). This categorical difference demonstrates a fundamental limitation in existing analyst reports: the complete absence of consideration for individual risk profiles, flexibility in analyses, or customized recommendations. In contrast, the AI-DSS integrated sophisticated volatility assessments through EGARCH modeling and provided perspectives tailored to risk-averse, risk-neutral, and risk-seeking investors. This underscores the artifact's innovative use of technical components, including natural language processing and data integration from heterogeneous sources such as Reddit API and LSEG-API, to enable truly personalized decision support.

For relevance and completeness, the AI-DSS achieved 4.7, surpassing traditional reports' average of 2.8 (difference: +1.9). The system's strengths included comprehensive coverage of critical aspects such as shareholder structure analysis and sentiment evaluation, with strong integration of diverse data sources. While data source integration received a lower weighting of 5% in the evaluation framework, the AI-DSS demonstrated superior performance even in this criterion. Traditional reports showed moderate relevance but frequently suffered from incomplete analyses, indicating that the AI-DSS's holistic approach more effectively minimizes information asymmetries by providing actionable and comprehensive information.

Finally, in efficiency and practicability, the AI-DSS achieved a perfect score of 5.0 against a mean of 2.9 for traditional reports (difference: +2.1), excelling particularly in user-friendliness through well-structured elements such as clear tables and logical sections. Although practical suitability received only 5% weighting as it was oriented toward future research applications, the results affirm the artifact's significant potential for real-world implementation in portfolio management and investment decision-making.

These results validate both Eval 3 (usability and robustness) and Eval 4 (effectiveness and practicality) by demonstrating the AI-DSS's objective superiority across all evaluation criteria. The findings directly support the research question through enhanced risk adjustment capabilities and indirectly validate the efficacy of technical components in reducing information asymmetries.

6.2 Summary of Quantitative Questionnaire Findings

The expert questionnaire involved 18 validated financial professionals who provided subjective validation of the AI-DSS artifact using Likert-scale assessments across three dimensions: report content quality, reduction of information asymmetries, and efficiency/practical usability. Bootstrap resampling techniques (B=1000/2000) ensured robust statistical estimates despite the modest sample size, demonstrating high confidence interval stability with 100% overlap between bootstrap iterations and strong reliability metrics (Cronbach's alpha ranging from 0.760 to 0.837; ordinal omega reaching 0.915).

In evaluating report content quality across 8 items, experts provided highly favorable ratings with an overall mean of approximately 4.11. The shareholder structure analysis received the highest rating (M=4.33, 95% CI [3.98, 4.69]), praised for its relevance and understandability in supporting risk-neutral investment decisions. The stock price analysis received the lowest rating in this category (M=3.83, CI [3.47, 4.20]) but still demonstrated a positive evaluation, indicating a clear presentation of technical trends and volatility assessments. Reliability metrics confirmed excellent scale homogeneity, with all corrected item-total correlations exceeding the 0.30 threshold and no problematic items identified.

The evaluation of information asymmetry reduction across 4 items received an overall mean of approximately 4.05, providing direct empirical support for the research hypothesis. The highest-rated aspect was the increase in transparency regarding financial situation, risks and market position (M=4.39, CI [4.07, 4.71]), demonstrating the system's effectiveness in addressing core information gaps. The provision of tailored information based on risk willingness received the lowest rating in this dimension (M=3.72, CI [3.37, 4.07]), suggesting opportunities for enhanced personalization capabilities. The combination of various analyses including ESG, fundamentals, and technical indicators, was particularly praised for eliminating information asymmetries (M=4.28, CI [4.01, 4.54]).

Efficiency and practical usability, evaluated across 4 items, achieved an overall mean of approximately 4.03. The system's efficiency in enabling faster decision-making processes received the highest rating (M=4.17, CI [3.88, 4.45]), indicating significant perceived value in workflow acceleration. Time savings compared to manual analysis scored 3.94, reflecting expert recognition of the system's automation benefits without quality compromise. Open-ended feedback highlighted particular strengths in data integration capabilities while noting ongoing challenges related to data availability and establishing trust in AI-generated recommendations.

The demographic profiles of participating experts confirmed their suitability for evaluation, with balanced distribution across experience levels (38.9% each for 2-5 years and >10 years) and regular engagement with analyst reports (50% using reports monthly or more frequently). These findings align with DSR evaluation phases Eval 3 and 4, substantiating the artifact's user-friendliness and effectiveness through comprehensive subjective assessment.

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6.3 Integration of Findings and Theoretical Implications

The integration of framework analysis and questionnaire results reveals highly complementary insights that strengthen the validity of the evaluation through methodological triangulation. The objective superiority of the AI-DSS in criteria such as risk adjustment and transparency is consistently echoed in experts' positive perceptions of asymmetry reduction and practical utility. This convergence of objective and subjective evidence enhances the validity of findings, fully addressing DSR quality requirements (Peffers et al., 2007; J. Venable et al., 2016) and providing robust empirical support for principal-agent theory applications (Eisenhardt, 1989) by demonstrating how the artifact effectively minimizes information gaps between investors and companies.

The research hypothesis - that AI-based DSS reduce information asymmetries and promote well-founded investment decisions through targeted data analysis - receives strong empirical support from both evaluation components. Framework analysis scores demonstrate superior risk-based customization capabilities, while questionnaire means consistently exceeding 4.0 across all dimensions confirm enhanced transparency, trust-building, and practical utility. The technical components underlying the system, including EGARCH models for volatility assessment and NLP algorithms for sentiment analysis, prove effective in integrating heterogeneous data sources, indirectly validating their critical role minimizing information asymmetries.

From a theoretical perspective, these results significantly extend existing literature on AI applications in financial decision-making (Araci, 2019; Bartelt & Röser, 2024a; Cao, 2021) by providing empirical evidence of DSR artifacts' potential to bridge theoretical frameworks with practical implementation. The findings demonstrate that sophisticated AI-DSS can effectively address longstanding challenges in financial markets related to information asymmetries and decision quality.

From a practical standpoint, the AI-DSS offers investors a demonstrably superior tool for informed decision-making, outperforming traditional analyst reports across all evaluated dimensions of efficiency, relevance, and customization. This performance differential suggests significant potential for democratizing access to high-quality investment analyses, particularly benefiting individual investors who previously lacked access to personalized, comprehensive analytical capabilities comparable to those available to institutional investors.

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6.4 Reflection on DSR Methodology and Quality Criteria

The evaluation approach employed in this research adheres to established DSR quality criteria, ensuring the validity and rigor of the artifact assessment. The methodological triangulation strategy successfully addresses key DSR quality dimensions (Peffers et al., 2007; J. Venable et al., 2016).

Relevance is demonstrated through the practical significance of addressing information asymmetries in financial markets, a well-documented problem validated through principal-agent theory and corresponding theories (Akerlof, 1970; Eisenhardt, 1989; Pratt & Zeckhauser, 1985; Shah, 2014; Spence, 1974). The artifact directly addresses real-world investor challenges, as evidenced by expert recognition of its practical utility (mean ratings >4.0 across all dimensions). The selection of evaluation criteria - transparency, risk adjustment, relevance and efficiency - directly corresponds to practitioner needs identified in current literature.

Rigor is ensured through multiple methodological safeguards. The framework analysis employs systematically derived criteria with transparent weighting schemes, while the quantitative evaluation utilizes validated psychometric approaches, including bootstrap resampling techniques and reliability assessment. The use of established methods such as EGARCH modeling and NLP processing, combined with high-quality data sources (LSEG-API, company documents), provides a solid technical foundation. The expert selection process, employing multi-criteria scoring and cross-validation, further strengthens methodological rigor.

Transparency is maintained through comprehensive documentation of all evaluation steps, from criteria development to statistical analysis. The bootstrap methodology with multiple iterations (B=1000/2000) and detailed confidence interval reporting ensures reproducible results. Detailed provider descriptions and methodological disclosure offset the anonymization of benchmark reports, which restricts certain aspects of transparency due to licensing constraints.

Validity is enhanced through the triangulation approach, which combines objective framework analysis with subjective expert assessment. The convergent findings across both evaluation methods strengthen construct validity, while the careful selection of evaluation criteria ensures content validity. The alignment of results with theoretical expectations regarding information asymmetry reduction supports criterion validity.

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Reliability is evidenced through strong internal consistency measures (Cronbach's alpha 0.760-0.837, ordinal omega up to 0.915) and stable bootstrap estimates with minimal observed-bootstrap deviations (0.002-0.010). The 100% confidence interval overlap between different bootstrapping iterations demonstrates the exceptional stability of the findings.

This methodological reflection confirms that the evaluation meets established DSR standards for scientific rigor while addressing practical relevance, providing a robust foundation for the artifact's validation and future development.

6.5 New Scientific Results

On the basis of the integrated evaluation results and their theoretical interpretation, the following new scientific results are formulated.

I. The dissertation demonstrates that investor risk preferences can be systematically operationalized within an AI-driven decision support architecture, thereby representing a methodologically grounded advancement over conventional analyst reports by addressing empirically identified deficiencies in transparency, risk personalization, and analytical integration. This approach facilitates structured, individualized single-stock investment analysis in accordance with regulatory suitability requirements.

II. The research validates a multi-layered analytical architecture integrating heterogeneous data sources - such as fundamental financial information, market time-series metrics, sentiment indicators, and risk measures - alongside various quantitative and qualitative methodologies, forming a coherent decision support architecture.

III. The empirical evaluation demonstrates that the structured integration of heterogeneous financial, technical, and sentiment-related data within a unified analytical process enhances transparency, risk alignment, analytical completeness, and practical usability compared to conventional analyst reports.

IV. Methodological triangulation, which integrates qualitative framework benchmarking with professional investment reports and quantitative expert validation, provides convergent empirical evidence for the robustness and internal consistency of this comprehensive multi-method analytical approach.

V. This dissertation contributes validated design knowledge regarding the systematic integration of diverse financial data, apply multiple analytical methods, and incorporate risk-based personalization within the Design Science Research framework for AI-based financial decision support systems.

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7 CONCLUSION AND OUTLOOK

Information asymmetry between investors and companies significantly affects single-stock investment decisions, as established by theories like PAT. This thesis therefore focuses on ways to reduce such asymmetries by implementing an AI-DSS.

The findings from the demonstration and evaluation phase of this thesis underscore the transformative potential of an AI-DSS in single stock investment decision-making. The research addresses two primary research questions (RQ1 and RQ2) and includes one hypothesis (H). Both were comprehensively assessed through methodological triangulation during the evaluation phase. This process included examining usability and robustness (Eval 3), as well as effectiveness and practicability (Eval 4), following the earlier stages of problem identification (Eval 1) and solution design (Eval 2). Detailed answers to RQ1 and RQ2 are provided below, supporting the validity of the hypothesis in this context; key evaluation items are *italicized.*

RQ1: Whether an AI-based DSS supports investment decisions based on investors' risk willingness?

In the context of the framework analysis, the category concerning *adjustments to risk willingness* is pertinent to this research question. This category is divided into three criteria (consideration of risk profiles, individualized decision support and flexibility of the analysis) where the report generated by the AI-DSS demonstrated superior performance compared to 11 traditional investment reports. When evaluating the *consideration of risk profiles* alongside *individualized decision support*, the report generated by the AI-DSS achieves a score of 4 out of 5 on the Likert scale - where 1 indicates no consideration and 5 denotes high consideration. Traditional reports score 1 out of 5, reflecting the lack of consideration for these relevant criteria. Regarding *flexibility*, which measures how well the report integrates multiple perspectives (such as short-term versus long-term risks or ESG versus financial stability), traditional reports scored 1 out of 5, while the AI-DSS report achieved a score of 3 out of 5. The framework analysis shows that traditional investment reports often overlook risk profiles, while AI-DSS reports more effectively support decisions tailored to the investor’s risk willingness.

Additionally, the expert questionnaire (N=18 proven experts) yields strong results for the research question. The *AI-DSS report provides risk-based information to guide investment choices*. This statement under review has a mean score of 3.72 out of 5; the 10% trimmed mean is 3.75, showing minimal bias from outliers. Bootstrapping (B=2,000) gives a 95% BCa-CI of [3.33, 4.00] and a trimmed CI of [3.38, 4.06], both reliably above negative ratings. This item supports scale reliability for reducing information asymmetries (α=0.760), with CITC values of 0.486 (Pearson) and 0.532 (polychoric). The results indicate that this item performs robustly and contributes meaningfully to the construct validity and internal consistency of the AI-DSS scale. Moreover, the recommended *course of action for investors with a particular risk willingness* is clearly articulated and well-supported by the underlying analyses, thereby enhancing the overall quality of decision-making. This methodology yielded an average score of 4.0 out of 5. Bootstrapping (B=2,000) produced a 95% BCa confidence interval of [3.56, 4.24] and a trimmed confidence interval of [3.62, 4.31], both of which are well above the threshold for negative ratings, indicating a consistently positive evaluation across respondents. The item demonstrates strong scale reliability in reducing information asymmetries (α=0.767), with corrected item-total correlation values of 0.805 (Pearson) and 0.935 (polychoric). Additionally, the generated report is applicable within specific analytical contexts, such as stock price analysis, shareholder structure, and fundamental analysis, particularly in relation to investor risk willingness.

Especially, *stock price analysis* achieved a mean score of 3.83 out of 5, with robustness affirmed by a 95% BCa confidence interval (B=2,000) of [3.39, 4.11]. The corrected item-total correlation (CITC, Pearson) of 0.473 demonstrates satisfactory discriminative capacity within the construct. For *shareholder structure*, the observed mean is higher (M = 4.33), and the 95% BCa-CI (B=2,000) [3.83, 4.57] confirms statistical stability and positive evaluation. The CITC (Pearson = 0.521) reflects good internal consistency with the overall reliability structure. Similarly, the *fundamental data* item yields a strong mean (M = 4.28), supported by a narrow 95% BCa-CI (B=2,000) of [3.94, 4.50], indicating low variance and stable estimation. The corresponding CITC (Pearson = 0.697) suggests a high contribution to the internal reliability of the AI-DSS scale.

The results indicate that the AI-DSS reports outstanding capabilities and performance as an analytical support tool for investor profiles across multiple analytical dimensions, demonstrating consistent and statistically reliable item characteristics. The results of the percentile and BCa bootstrap methods are very similar, which indicates stable and reliable estimates. The deviations between observed values and bootstrap means are minimal (e.g., abs(obs−boot) [2k] ≈ 0.000−0.005 for the items mentioned), and the CI overlap between B=1,000 and B=2,000 resamples is 100.0%, which reflects excellent estimation stability.

Furthermore, the reliability analyses (Cronbach's α) show very good values across all scales (α = 0.837, 0.760, 0.767), consistent with existing literature, each confirmed by narrow bootstrap confidence intervals. The corresponding ordinal reliability coefficients (α = 0.915, 0.838, 0.823) and Omega values (Ω = 0.915, 0.845, 0.837) further underline the strong internal consistency and robustness of the measurement model, indicating that the applied scales perform excellently and provide a highly reliable basis for evaluating the AI-DSS's analytical quality.

In summary, RQ1 has been substantiated: the developed AI-DSS effectively customizes investment reports according to individual investors' risk preferences, facilitating data-driven and evidence-based decision-making. The findings indicate that the system delivers adaptive analyses that reduce decision-making biases and offer a level of personalization uncommon in conventional investment reports. Additionally, the AI-DSS reliably supports single-stock investment decisions in accordance with investors' risk tolerance.

RQ2: Which technological components are crucial for providing customized information on individual securities regarding information asymmetries?

The AI-DSS integrates heterogeneous data sources and algorithms to generate investment reports through its architectural framework - for example, employing EGARCH for volatility modeling, NLP techniques for sentiment analysis, utilizing pandas for data processing, and LLMs for further contextualization. The evaluation demonstrates that the AI-DSS report received exceptional ratings for its provision of tailored information on individual securities, particularly in addressing information asymmetries. This performance can be directly attributed to the underlying architecture supporting each report's generation.

The framework analysis results are organized into four topics (*completeness of the analysis*, *integration of heterogeneous data sources*, *disclosure of risks and uncertainties and clarity*) related to RQ2. The initial topic concerns the *completeness of the analysis*, which is a key component of the AI-DSS. The report produced by the AI-DSS (coverage of share price, ESG, fundamentals, etc.) received a completeness score of 5 out of 5, while traditional investment reports had an average score of 2.82. For relevance, AI-DSS reports were rated 5 out of 5, compared to an average of 2.55 for conventional reports. Regarding the *integration of heterogeneous data sources*, the AI-DSS report scored 4 out of 5, whereas traditional reports averaged 3.09 out of 5. According to the framework analysis results, the AI-DSS report consistently received higher scores across all categories. Subsequent topics address

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advanced algorithmic elements within the AI-DSS, beginning with volatility modeling algorithms such as EGARCH and NLP. The AI-DSS report was given a score of 5 out of 5 for *disclosure of risks and uncertainties*, while traditional investment reports averaged 2.36. In terms of risk profile consideration, it received a score of 4 out of 5, compared to an average of 1.00 for conventional reports. The use of NLP and LLMs for sentiment analysis and contextualization resulted in a *clarity* score of 4 out of 5, versus an average of 3.27. As previously noted, these components play a critical role in minimizing information asymmetries. The framework analysis shows that AI-DSS consistently excels in personalization and transparency.

In addition to framework analysis, the previously referenced expert questionnaire (N=18) produces robust findings for RQ2. The AI-DSS report delivers *customized information to investors according to their risk preferences*, thereby enabling more informed decision-making. This statement under review has a mean score of 3.72 out of 5; the 10% trimmed mean is 3.75, showing minimal bias from outliers. Bootstrapping (B=2,000) gives a 95% BCa-CI of [3.33, 4.00] and a trimmed CI of [3.38, 4.06], both reliably above negative ratings. This item supports scale reliability for reducing information asymmetries (α=0.760), with CITC values of 0.486 (Pearson) and 0.532 (polychoric). Moreover, the *combination of various analyses* (e.g., stock price, ESG, fundamental data) conveys a comprehensive picture that effectively minimizes information asymmetries. This methodology yielded an average score of 4.28 out of 5. Bootstrapping (B=2,000) produced a 95% BCa confidence interval of [4.00, 4.50] and a trimmed confidence interval of [4.00, 4.56], both of which are well above the threshold for negative ratings. The item demonstrates strong scale reliability in reducing information asymmetries (α=0.760), with corrected item-total correlation values of 0.528 (Pearson) and 0.676 (polychoric). Additionally, the report enhances *transparency regarding the financial situation, risks, and market position*, thereby reducing information asymmetries. The observed mean is high (M = 4.39), and the 95% BCa-CI (B=2000) [4.00, 4.61] confirms statistical stability and positive evaluation. The CITC (Pearson = 0.620) reflects significant internal consistency with the overall reliability structure. The report *addresses potential uncertainties* (e.g., profitability declines, market volatility) sufficiently to strengthen investor confidence. Remarkably, this item achieved a mean score of 3.83 out of 5, with robustness affirmed by a 95% BCa confidence interval (B=2,000) of [3.39, 4.11]. The corrected item-total correlation (CITC, Pearson) of 0.625 demonstrates satisfactory dis-

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criminative capacity within the construct. For *stock price analysis* (e.g., trend analysis, volatility, risk assessment), which leverages components like EGARCH, the mean score is 3.83 out of 5, supported by a narrow 95% BCa-CI (B=2,000) of [3.39, 4.11], indicating low variance and stable estimation. The corresponding CITC (Pearson = 0.473) suggests a solid contribution to the internal reliability of the AI-DSS scale. Similarly, the *sentiment analysis and analyst ratings* item, incorporating NLP techniques, yields a mean (M = 4.17), with a 95% BCa-CI (B=2,000) of [3.89, 4.33]. The CITC (Pearson = 0.396) contributes to scale consistency. The *fundamental data* item (e.g., profitability, stability, forecasts), utilizing tools like pandas, has a strong mean (M = 4.28), affirmed by a 95% BCa-CI (B=2,000) of [3.94, 4.50]. And the CITC (Pearson = 0.697) indicates high discriminative power. Finally, the ESG assessment, enhanced by LLM contextualization, scores a mean of 4.17, with a 95% BCa-CI (B=2,000) of [3.72, 4.44] and CITC (Pearson = 0.489), further underscoring the architecture's role in customized information delivery.

Results from the questionnaire corroborated these findings: experts rated content quality at around 4.11/5 (≈82.2%; 4.28/5 or 85.6% for holistic views) and efficiency and utility at around 4.03/5 (≈80.6%; $\alpha = 0.767$–0.837; CIs overlapped fully). These findings underscore the methodological robustness of the DSR triangulation approach, which integrates structured criteria matrices with bootstrapped questionnaire methods.

Overall, RQ2 is confirmed: the technological components previously discussed within the architecture of the AI-DSS effectively reduce information asymmetries and deliver tailored information on individual securities. Convergent findings from RQ1 and RQ2 allow empirical testing of whether AI-based DSS reduce information asymmetries.

Hypothesis (H): "AI-based DSS reduce information asymmetries(ΔI) by analyzing data in a targeted manner and minimizing the discrepancy between V_F and V_I."

The AI-DSS demonstrates capabilities in reducing information asymmetries through targeted data analysis and minimizing discrepancies between firm value (V_F) and investor-perceived value (V_I) in single stock investments.

In the context of the framework analysis, the categories concerning transparency and relevance and completeness are particularly pertinent to this hypothesis, as they address the reduction of information gaps via clear, comprehensive, and integrated disclosures. This category is divided into criteria such as *clarity and comprehensibility*, *disclosure of risks and uncertainties*, and *comprehensibility of recommendations for transparency*, where the report

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generated by the AI-DSS achieved scores of 4, 5, and 4 out of 5, respectively. Traditional reports had mean scores of 3.27, 2.36, and 2.27, highlighting the AI-DSS's superior performance in minimizing asymmetries through enhanced transparency. For *relevance* and *completeness*, criteria include *completeness of analyses*, *relevance for investment decisions*, and *integration of different data sources*, with AI-DSS scores of 5, 5, and 4 compared to traditional means of 2.82, 2.55, and 3.09. The framework analysis indicates that traditional investment reports often lack depth in addressing uncertainties and integrating data, while AI-DSS reports more effectively minimize ΔI by providing targeted, comprehensive insights that align V_F and V_I.

Furthermore, the expert questionnaire (N=18) provides strong evidence in favor of the hypothesis. The *Ratings on the Reduction of Information Asymmetries* scale directly assesses the AI-DSS's capacity to reduce informational imbalances between investors and the market. For example, the item concerning *enhancing transparency in the company's financial condition, risk exposure, and market position to minimize information asymmetries* received a mean score of 4.39. The 10% trimmed mean was slightly higher at 4.44, indicating that the influence of outliers is minimal. Bootstrapping (B=2,000) gives a 95% BCa-CI of [4.00, 4.61] and a trimmed CI of [4.00, 4.69], both reliably above neutral ratings. This item supports scale reliability (α=0.760), with CITC values of 0.620 (Pearson) and 0.775 (polychoric). It was observed that the report appeared to *address potential uncertainties (e.g., profitability declines, market volatility)* in a manner perceived as sufficient to strengthen investor confidence. The item yielded a mean of 3.83, with a 95% BCa-CI (B = 2,000) of [3.39, 4.11] and a trimmed CI of [3.50, 4.19], suggesting consistently positive evaluations. The CITC (Pearson=0.625, polychoric=0.709) reflects strong contribution to construct validity. It was found that the report appeared to *provide tailored information enabling investors to make informed decisions aligned with their individual risk willingn*ess. This item yielded a mean of 3.72, with a 95% BCa-CI [3.33, 4.00] and a trimmed CI [3.38, 4.06], alongside CITC values (Pearson = 0.486, polychoric = 0.532).

Furthermore, the c*ombination of various analyses (e.g., stock price, ESG, and fundamental data)* was perceived as conveying a *comprehensive picture that effectively reduces information asymmetries*. This item achieved a mean of 4.28, with a 95% BCa-CI [4.00, 4.50] and a trimmed CI [4.00, 4.56], accompanied by CITC values (Pearson = 0.528, polychoric = 0.676).

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These items collectively underscore the AI-DSS's targeted data analysis in minimizing discrepancies between V_F and V_I. Moreover, complementary items from other scales appeared to reinforce this tendency. Specifically, the AI-DSS report was perceived as *offering a comprehensive and transparent overview of the company* (e.g., market position, financial data, ESG performance), yielding a mean of 4.17 with a 95% BCa-CI [3.67, 4.44]. Likewise, the risk analysis contained in the AI-DSS report was viewed as relevant and presented in a comprehensible manner that facilitates the evaluation of the *company's risk situation* (M = 3.94, BCa-CI [3.50, 4.28]). Both items contribute to the reduction of information asymmetries through structured and evidence-based insights. These results indicate that the AI-DSS exhibits outstanding capabilities in reducing ΔI across analytical dimensions, demonstrating consistent and statistically reliable item characteristics. Moreover, the percentile and BCa bootstrap methods are very similar, which indicates stable and reliable estimates. The deviations between observed values and bootstrap means are minimal (e.g., abs(obs−boot) [2k] ≈ 0.002−0.003 for the key items), and the CI overlap between B=1,000 and B=2,000 resamples is 100.0%, which reflects excellent estimation stability. Furthermore, the reliability analyses (Cronbach's α) show good values for the asymmetry reduction scale (α=0.760), confirmed by narrow bootstrap confidence intervals [0.548, 0.851]. The corresponding ordinal reliability coefficients (α=0.838) and Omega values (Ω=0.845) further underline the strong internal consistency and robustness of the measurement model, indicating that the applied scales perform well and provide a reliable basis for evaluating the AI-DSS's role in minimizing information discrepancies. Summarizing, the findings are consistent with the hypothesis that AI-based DSS can reduce information asymmetries (ΔI) by conducting targeted data analyses that minimize the discrepancy between firm value (V_F) and investor-perceived value (V_I). The empirical evidence lends strong support to this theoretical assumption, while remaining open to further examination under alternative market conditions and investor contexts.

In conclusion, the findings across RQ1, RQ2, and the confirmed hypothesis collectively demonstrate that the AI-DSS constitutes a robust and empirically validated framework for enhancing single-stock investment decision-making. By combining adaptive analytical mechanisms with a modular technological architecture, the system effectively tailors its outputs to investors' individual risk profiles while simultaneously minimizing information asymmetries through transparent and data-driven analyses. Qualitative framework evaluation and quantitative expert assessments indicate the methodological soundness and practical

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relevance of the AI-DSS approach. The results show that integrating AI-based components such as volatility modeling, NLP-driven sentiment analysis, and contextualization through large language models leads to measurable changes in the personalization of investment recommendations. Finally, this integration significantly enhances the reliability and interpretability of these recommendations.

As an outlook, future research should focus on the generalization of the foregoing promising results by expanding the analytical and empirical scope of AI-DSS in financial markets:

i. Building on these results, one avenue is to conduct longitudinal studies tracking how AI-DSS tools affect changes in investors' portfolios and risk profiles over time. Such studies could provide insights into the persistence of behavioral changes, adaptive learning processes, and the actual portfolio effects arising from AI-assisted recommendations.
ii. To extend the applicability of existing AI-DSS, personalized integration approaches can be developed, for instance by enabling users to upload their own portfolios. This would allow an in-depth assessment of the fit between portfolio composition, individual risk willingness, and potential optimization scenarios, supporting more evidence-based financial behavior. Likewise, ETF look-through analyses should be incorporated to investigate the underlying asset structures of funds (e.g., DAX, MSCI World) and their alignment with different investor risk preferences. This can be used to assess diversification efficiency and exposure across different sectors or geographic regions, providing additional data for the AI-DSS.
iii. Peer group and sector-based comparisons can be performed to identify key performance indicators and benchmarking trends that may inform adaptive AI-DSS recommendations. Incorporating these capabilities enables the AI-DSS to conduct advanced analyses of individual stocks, including comparative evaluations against competitors. On a methodological level, future work could integrate reinforcement learning or hybrid explainable AI architectures to further enhance transparency, interpretability, and responsiveness to user feedback.
iv. In line with current developments, future studies should further strengthen the consideration of ethical and regulatory dimensions, such as algorithmic fairness, explainability, and accountability, in line with frameworks like the EU AI Act and established financial advisory standards. Addressing these aspects is essential for ensuring

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trustworthiness and societal acceptance of AI-driven decision support in financial markets.

In summary, AI-DSS' represent a pivotal step toward more transparent, inclusive, and evidence-oriented financial ecosystems. By effectively integrating AI with human financial judgment, such systems can bridge informational asymmetries, mitigate cognitive biases, and promote fairer and more rational investment decisions. The AI-DSS developed and evaluated in this thesis demonstrates that advanced analytical architectures - combining volatility modeling, natural language processing, and contextual reasoning - generates significant improvements in personalization, interpretability, and decision quality. Beyond their analytical value, AI-DSS frameworks contribute strongly to the broader evolution of responsible and ethically aligned AI within finance, offering a foundation for sustainable innovation and enhanced investor empowerment.

SUMMARY

This thesis addresses the minimization of information asymmetries in financial markets through the development of an AI-DSS for single-stock investments, employing PAT as the theoretical framework. At its core lies the question of how information asymmetries can be reduced and such a system can optimize investment decisions based on individual risk preferences and which technological components are necessary to provide tailored information on individual securities. The system enables the determination of investor preferences in accordance with MiFID II, analyzes specific stocks via their ISIN, and generates customized investment reports that integrate financial, technical, and sentiment analyses. The central hypothesis posits that AI-DSSs reduce information asymmetries by minimizing the discrepancy between the investor's perceived value and the true company value.

Methodologically, the research follows a DSR approach with a single build phase, focusing on evaluation levels of solution instantiation and practical application, as the problem definition is already grounded in PAT. The AI-DSS architecture comprises four interconnected layers: first, the Input Layer captures ISIN and risk preferences through a MiFID II-compliant questionnaire that scores responses across two dimensions (risk tolerance and risk willingness). Second, the Data Analysis Layer integrates heterogeneous sources, including LSEG APIs for up to ten years of fundamental data and prices, SERP for one-year annual reports, and Reddit for seven-day sentiment data, as well as commodity and foreign exchange quotes over a one-year period with a 21-day rolling window. Third, the scoring layer applies weighted aggregation of category-specific scores normalized to the interval from 0 to 5, utilizing models such as EGARCH (1,1,1) for volatility quantification with an asymmetry parameter of 0.1547 and Value-at-Risk calculations at confidence levels of 95%, 99%, and 99.9%. Fourth and finally, the output layer employs an MAS and LLM to synthesize PDF reports that ensure regulatory compliance. The technical implementation relies on Python libraries such as Pandas and FastAPI, while FinBERT is used for sentiment classification and RAG for risk management analysis.

The results demonstrate the superior performance of the developed system through methodological triangulation. And the comparison with eleven professional investment reports shows a very good aggregated score of 4.35 out of 5 for the AI-DSS against a benchmark average of 2.22, representing a difference of 2.13 points. Particularly notable are the advantages in transparency (4.3 versus 2.6), risk adjustment (3.7 versus 1.0), relevance and completeness (4.7 versus 2.8), and efficiency (5.0 versus 2.9).

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The quantitative expert questionnaire with 18 participants yields mean values of 4.11 out of 5 for content quality, 4.05 out of 5 for the reduction of information asymmetries- with transparency improvement particularly standing out at 4.39 out of 5 - and 4.03 out of 5 for efficiency and usability. The reliability of measurements proves robust with Cronbach's alpha values between 0.760 and 0.837, while stable bootstrap confidence intervals with complete overlap and relative widths of 0.149 to 0.188 underscore the stability of the results. These findings supporting the initial hypothesis and demonstrate that targeted analyses reduce information asymmetries and improve decision-making, particularly for risk-neutral investor profiles.

This research empirically substantiates the theoretical assumption that AI-DSS' can effectively minimize informational asymmetries and cognitive biases, thereby fostering more rational, transparent, and evidence-oriented decision processes in financial markets.

To advance generalization and practical applicability, future research can

i. enable portfolio-specific integrations allowing investors to assess the alignment between individual portfolio structures, risk willingness, and optimization scenarios;
ii. conduct ETF look-through analyses by decomposing underlying holdings and mapping them to personalized risk profiles; and
iii. explore peer group and sector-based benchmarking to derive adaptive, data-driven recommendation patterns.
iv. Moreover, ethical and regulatory dimensions-particularly algorithmic fairness and explainability - remain central in light of evolving frameworks such as the EU AI Act and established financial advisory standards.

In summary, AI-DSS constitute a pivotal step toward more accountable, and inclusive aligned financial ecosystems. By combining analytical precision with human financial judgment, the developed and evaluated AI-DSS not only materialize transparency and trust, and they are a sustainable transformation from unsure to aware decision-making with evaluated information in modern financial markets.

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APPENDIX

Appendix I: EGARCH Model Parameters and Backtesting Results

EGARCH Model Parameters:

mu -0.017339

omega 0.112931

alpha[1] -0.060639

gamma[1] 0.154650

beta[1] 0.747879

nu 4.999365

Backtesting Results (Number of Exceedances):

Confidence Level 95.0%: Expected = 25.0, Parametric = 24, EGARCH = 8

Confidence Level 99.0%: Expected = 5.0, Parametric = 3, EGARCH = 2

Confidence Level 99.9%: Expected = 0.5, Parametric = 0, EGARCH = 0

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Appendix II: Analysis of the given Investment Reports

Category	Criterion	Rating	Weighting (in %)	Report 1	2	3	4	5	6	7	8	9	10	11	AI-DSS
Transparency	1.1 Clarity and comprehensibility	1 (very unclear) to 5 (very clear)	10	2	3	3	4	2	4	4	4	4	4	2	4
Transparency	1.2 Disclosure of risks and uncertainties	1 (no disclosure) to 5 (full disclosure)	10	4	2	1	2	1	3	2	4	4	2	1	5
Transparency	1.3 Comprehensibility of the recommendation	1 (not comprehensible) to 5 (very comprehensible)	10	4	2	2	1	1	4	1	2	5	2	1	4
Adjustment to risk willingness	2.1 Consideration of risk profiles	1 (no consideration) to 5 (strong consideration)	10	1	1	1	1	1	1	1	1	1	1	1	4
Adjustment to risk willingness	2.2 Individualized decision support	1 (not individualized) to 5 (highly individualized)	10	1	1	1	1	1	1	1	1	1	1	1	4
Adjustment to risk willingness	2.3 Flexibility of the analyses	1 (no flexibility) to 5 (high flexibility)	10	1	1	1	1	1	1	1	1	1	1	1	3

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Category	Criterion	Rating	Weighting (in %)	Report											
				1	2	3	4	5	6	7	8	9	10	11	AI-DSS
Relevance and completeness	3.1 Completeness of the analyses	1 (very incomplete) to 5 (very complete)	10	4	3	2	2	2	3	4	3	4	3	1	5
Relevance and completeness	3.2 Relevance for investment decisions	1 (not relevant) to 5 (very relevant)	10	3	2	2	2	2	3	3	3	4	3	1	5
Relevance and completeness	3.3 Integration of different data sources	1 (no integration) to 5 (strong integration)	5	3	2	3	3	2	4	4	4	4	3	2	4
Efficiency and practicability	4.1 User-friendliness	1 (not user-friendly) to 5 (very user-friendly)	10	3	3	2	3	2	4	4	4	5	2	2	5
Efficiency and practicability	4.2 Practical suitability	1 (not suitable for practical use) to 5 (very suitable for practical use)	5	3	2	1	3	2	3	3	4	4	3	1	5
Overall Score			100	2,6	2	1,7	2	1,5	2,75	2,45	2,7	3,3	2,2	1,25	4,35

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Appendix III: Statistical Metrics Derived from the Quantitative Questionnaire Regarding the Investment Report of the AI-DSS

Item-rest correlations (CITC)

Item	CITC Pearson	CITC polychoric	Flag (<0.30)
The AI-DSS report provides a comprehensive and transparent overview of Mercedes-Benz Group AG (e.g., market position, financial data, ESG performance).	0.706	0.821	
The ESG (environmental, social, governance) assessment in the AI-DSS report is understandable and relevant for investors who consider sustainability.	0.489	0.634	
The analysis of sentiment and analyst ratings in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions.	0.396	0.499	
The analysis of the shareholder structure (e.g., institutional ownership, free float) in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions from the perspective of a risk-neutral investor.	0.521	0.702	
The fundamental data (e.g., profitability, stability, forecasts) in the AI-DSS report is well structured and facilitates the assessment of the company's financial health from the perspective of a risk-neutral investor.	0.697	0.863	
The overall risk analysis in the AI-DSS report provides a comprehensive overview of the assessment of individual report components and facilitates understanding of the risk classification.	0.787	0.971	
The risk analysis in the AI-DSS report is relevant and presented in a comprehensible manner, facilitating the assessment of the company's risk situation.	0.626	0.721	
The stock price analysis (e.g., trend analysis, volatility, risk assessment) in the AI-DSS report is clearly presented and supports investors with a risk-neutral risk profile in their decision-making.	0.473	0.576	
The combination of various analyses (e.g., share price, ESG, fundamental data) provides a comprehensive picture that effectively eliminates information asymmetries."	0.528	0.676	

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Item	CITC Pearson	CITC poly-choric	Flag (<0.30)
The report adequately addresses potential uncertainties (e.g., declines in profitability, market volatility) to strengthen investor confidence.”	0.625	0.709	
The report increases transparency regarding the financial situation, risks, and market position of Mercedes-Benz Group AG, thereby reducing information asymmetries.	0.620	0.775	
The report provides tailored information that helps investors make informed decisions based on their risk willingness.	0.486	0.532	
The AI-DSS report saves time compared to a manual analysis without compromising transparency or quality.	0.516	0.528	
The recommended course of action for risk-neutral investors is comprehensible and justified by the analyses, which improves the quality of decision-making.	0.805	0.935	
The report is efficient and enables faster decision-making for investors.	0.433	0.543	
The report is useful and practical for investors in practice (e.g., portfolio management, investment decisions).	0.605	0.617	

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Reliability and Trimmed Mean (10%) Analysis

Item	n	tMean (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs (obs−boot) [1k]	abs (obs−boot) [2k]
The AI-DSS report provides a comprehensive and transparent overview of Mercedes-Benz Group AG (e.g., market position, financial data, ESG performance).	18	4.25	[3.81, 4.56]	[3.81, 4.62]	[3.75, 4.56]	[3.75, 4.56]	0.021	0.025
The ESG (environmental, social, governance) assessment in the AI-DSS report is understandable and relevant for investors who consider sustainability.	18	4.19	[3.81, 4.56]	[3.81, 4.56]	[3.75, 4.50]	[3.69, 4.50]	0.001	0.004
The analysis of sentiment and analyst ratings in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions.	18	4.19	[3.94, 4.38]	[3.94, 4.44]	[3.94, 4.44]	[3.94, 4.44]	0.025	0.021
The analysis of the shareholder structure (e.g., institutional ownership, free float) in the AI-DSS report is relevant and presented in an understandable manner, facilitating investment decisions from the perspective of a risk-neutral investor.	18	4.44	[4.00, 4.69]	[4.06, 4.69]	[4.06, 4.69]	[4.06, 4.69]	0.049	0.043
The fundamental data (e.g., profitability, stability, forecasts) in the AI-DSS report is well structured and facilitates the assessment of the company’s financial health from the perspective of a risk-neutral investor.	18	4.31	[4.06, 4.56]	[4.00, 4.56]	[4.00, 4.50]	[4.00, 4.56]	0.019	0.023
The overall risk analysis in the AI-DSS report provides a comprehensive overview of the assessment of individual report components and facilitates understanding of the risk classification.	18	4.00	[3.75, 4.25]	[3.81, 4.25]	[3.69, 4.14]	[3.69, 4.12]	0.005	0.002
The risk analysis in the AI-DSS report is relevant and presented in a comprehensible manner, facilitating the assessment of the companys risk situation.	18	4.00	[3.56, 4.38]	[3.56, 4.38]	[3.55, 4.38]	[3.50, 4.38]	0.017	0.024
The stock price analysis (e.g., trend analysis, volatility, risk assessment) in the AI-DSS report is clearly presented and supports investors with a risk-neutral risk profile in their decision-making.	18	3.88	[3.50, 4.19]	[3.50, 4.19]	[3.48, 4.19]	[3.44, 4.19]	0.025	0.014

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Statistic	Type / Method	Value / Interval	Sample / Parameters
Cronbach's α (observed)	Classical (inter-item)	0.837	N = 18, k = 8
95% Confidence Interval	Bootstrap (B = 1000)	[0.583, 0.919]	
	Bootstrap (B = 2000)	[0.607, 0.921]	
Cronbach's α (ordinal)	Polychoric correlations (R_poly)	0.915	
McDonald's ω (ordinal)	Polychoric correlations	0.915	

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Item	n	tMean (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs(obs−boot) [1k]	abs(obs−boot) [2k]
The combination of various analyses (e.g., share price, ESG, fundamental data) provides a comprehensive picture that effectively eliminates information asymmetries.	18	4.31	[4.06, 4.56]	[4.00, 4.56]	[4.06, 4.56]	[4.00, 4.56]	0.025	0.019
The report adequately addresses potential uncertainties (e.g., declines in profitability, market volatility) to strengthen investor confidence.	18	3.88	[3.44, 4.25]	[3.50, 4.19]	[3.44, 4.25]	[3.50, 4.19]	0.021	0.027
The report increases transparency regarding the financial situation, risks and market position of Mercedes-Benz Group AG, thereby reducing information asymmetries.	18	4.44	[4.06, 4.75]	[4.06, 4.75]	[4.00, 4.69]	[4.00, 4.69]	0.011	0.017
The report provides tailored information that helps investors make informed decisions based on their risk willingness.	18	3.75	[3.38, 4.06]	[3.38, 4.06]	[3.38, 4.06]	[3.38, 4.06]	0.014	0.017

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Statistic	Type / Method	Value / Interval	Sample / Parameters
Cronbach's α (observed)	Classical (inter-item)	0.760	N = 18, k = 4
95% Confidence Interval	Bootstrap (B = 1000)	[0.552, 0.853]	
	Bootstrap (B = 2000)	[0.548, 0.851]	
Cronbach's α (ordinal)	Polychoric correlations (R_poly)	0.838	
McDonald's ω (ordinal)	Polychoric correlations	0.845	

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Item	n	tMean (obs)	Percentile CI [1k]	Percentile CI [2k]	BCa CI [1k]	BCa CI [2k]	abs(obs−boot) [1k]	abs(obs−boot) [2k]
The AI-DSS report saves time compared to a manual analysis without compromising transparency or quality.	18	4.00	[3.44, 4.50]	[3.44, 4.44]	[3.28, 4.38]	[3.31, 4.38]	0.005	0.002
The recommended course of action for risk-neutral investors is comprehensible and justified by the analyses, which improves the quality of decision-making.	18	4.06	[3.69, 4.38]	[3.69, 4.38]	[3.62, 4.31]	[3.62, 4.31]	0.022	0.025
The report is efficient and enables faster decision-making for investors.	18	4.19	[3.88, 4.50]	[3.88, 4.50]	[3.81, 4.44]	[3.81, 4.44]	0.005	0.009
The report is useful and practical for investors in practice (e.g., portfolio management, investment decisions).	18	4.06	[3.62, 4.44]	[3.62, 4.44]	[3.62, 4.38]	[3.62, 4.38]	0.028	0.025

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Statistic	Type / Method	Value / Interval	Sample / Parameters
Cronbach's α (observed)	Classical (inter-item)	0.767	N = 18, k = 4
95% Confidence Interval	Bootstrap (B = 1000)	[0.335, 0.903]	
	Bootstrap (B = 2000)	[0.319, 0.901]	
Cronbach's α (ordinal)	Polychoric correlations (R_poly)	0.823	
McDonald's ω (ordinal)	Polychoric correlations	0.837	

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Appendix IV: Sample Report created by the AI-DSS

This report has been produced by the AI-DSS in accordance with the methodology outlined in the referenced thesis. In compliance with licensing requirements, company-specific information has either been omitted or anonymized. All content is derived from publicly accessible sources, and any restricted data has been concealed. The report comprises all sections cited in the thesis, with the exception of the management summary and the cover and back cover pages. The version utilized for framework analysis and the expert questionnaire is available upon request.

This stock analysis was created as part of a scientific research project. It is intended solely for information and research purposes and does not constitute investment advice within the meaning of the Securities Trading Act (WpHG), nor does it constitute a buy or sell recommendation or any other financial, tax, or legal advice. It does not replace individual consultation with a financial, tax, or legal advisor.

The information contained in this analysis is based on publicly available data and scientific methods and has been researched with the greatest possible care. However, no guarantee can be given for the accuracy, completeness, or timeliness. Past developments or forecasts are based on assumptions that may change significantly due to market changes, regulatory changes, or other external factors.

There is no guarantee for future market developments or investment success. Neither the authors nor the institutions or companies involved assume any liability for financial losses or other damages that result directly or indirectly from the use of or reliance on this analysis.

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Technical Analysis

The recent 5-day trading period for the asset has shown a **percentual change: -2.33%**, which might initially seem concerning for a risk-seeking investor. However, the **trading range: 3.92%** between the **highest price:** [redacted] **EUR** and the **lowest price:** [redacted] **EUR** indicates a level of price movement that could offer potential opportunities for those looking to capitalize on short-term fluctuations. The closing prices over the last five days were 59.79 EUR, 59.44 EUR, 58.77 EUR, 58.45 EUR, and 58.36 EUR, reflecting a consistent downward trend in closing values. This trend might appeal to investors seeking to buy at lower prices in anticipation of a rebound.

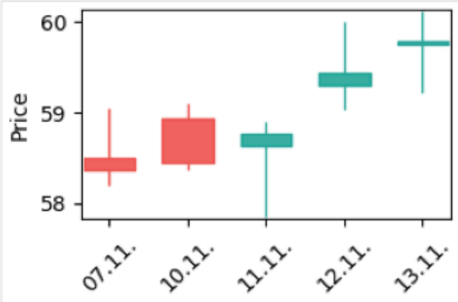

Abbildung 1: Kursverlauf [redacted] *der letzten 5 Handelstage*

When examining the volatility data, the **10-day volatility: 21.36%** and the **30-day volatility: 23.25%** suggest a relatively high level of recent price variability, which can be attractive to risk-seeking investors who thrive on short-term opportunities. The **60-day volatility: 20.52%** and the **90-day volatility: 24.31%** further illustrate that the asset has experienced significant price movements over a longer period, maintaining a consistent level of volatility that could be beneficial for those looking to engage in active trading strategies. Overall, the combination of recent price declines and persistent volatility presents a potentially lucrative environment for investors with a high risk tolerance and a preference for dynamic market conditions.

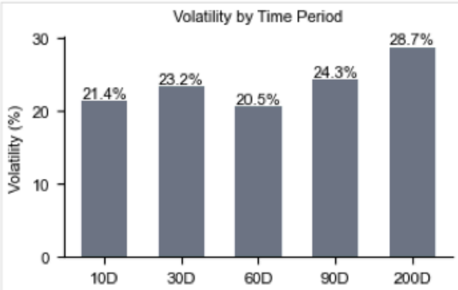

Abbildung 2: Volatilitätsanalyse [redacted]

For a risk-seeking investor, the portfolio's performance metrics indicate a promising yet volatile opportunity. The daily return of **0.32%** and an impressive **annualized return of 81.76%** suggest significant potential gains. However, the **Sharpe Ratio: 0.17** and **Sortino Ratio: 0.57** reveal that these returns come with considerable risk, as the low ratios indicate limited risk-adjusted returns. The **Maximum Drawdown: -0.04%** is minimal, suggesting that the portfolio has not experienced severe losses historically, which may

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appeal to risk-tolerant investors. On the risk measurement side, the **Value at Risk (95%): -2.69%** and **Value at Risk (99%): -3.72%** highlight potential losses under adverse market conditions, while the **daily standard deviation: 1.93%** and **annualized volatility: 30.59%** indicate high variability in returns. The **Beta: 1.02** suggests that the portfolio's movements are slightly more volatile than the market, aligning with the risk-seeking nature of the investor. Overall, while the potential for high returns exists, investors must be prepared for significant volatility and potential losses.

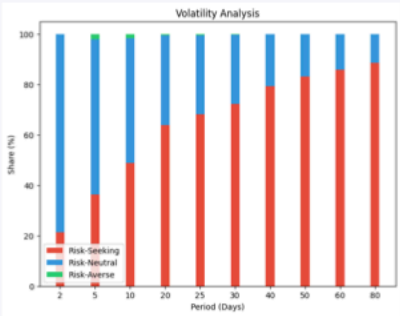

Figure 3: Volatility Analysis by Risk Type

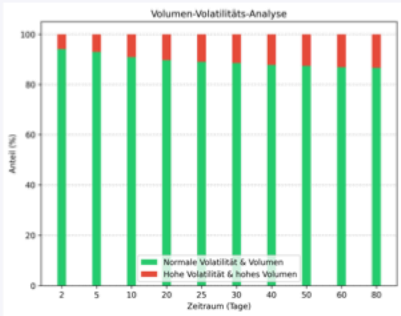

Figure 4: Volume-Volatility Analysis by Risk Type

Volatility Analysis

The volatility analysis examines price fluctuations of the stock across different time periods. The risk profile of the stock is determined based on the strength and frequency of these fluctuations.

The volatility analysis over ten periods indicates that the stock exhibits significant fluctuations, with a dominant risk-seeking behavior observed in 64.7% of the cases. This profile suggests that the stock is more suitable for risk-tolerant investors, as its higher volatility reflects a higher risk appetite and potential for greater returns, making it less appropriate for risk-averse or risk-neutral investors seeking stability.

Volume-Volatility Analysis

The volume-volatility analysis considers the interplay between trading volume and price fluctuations. This combined view enables a more precise assessment of market activity and associated risk.

The volume-volatility analysis over the 10-period timeframe indicates a relatively modest combined activity level of 10.7%, suggesting limited market engagement and moderate price fluctuations. This profile points to a relatively stable trading pattern, making the stock more suitable for risk-averse investors seeking lower volatility and consistent performance.

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Fundamental Analysis

Performance Metrics

The performance metrics provide a mixed picture of strengths and weaknesses. Revenue Growth over the last 10 years is 5.88%, which exceeds the 5% threshold, indicating long-term stability in revenue generation. The short-term 3-year Revenue Growth is even stronger at 8.58%, suggesting accelerated growth in recent years, which is a positive indicator for future revenues. EBIT Growth over the last 10 years, however, is only 2.30%, which falls short of the 5% benchmark, indicating a potential area of concern regarding the company's ability to grow its operating income. The 3-year EBIT Growth is negative at -5.44%, highlighting a troubling recent decline in operating earnings. The EBIT Drawdown of 50.15% is significantly higher than the desired threshold of 30%, reflecting vulnerability in maintaining consistent operating profits. The Return on Capital Employed (ROCE) is 6.39%, well below the 15% benchmark, pointing to inefficiencies in capital utilization. Similarly, the Return on Equity (ROE) is 14.07%, slightly below the 15% threshold, suggesting that the company is close to, but not quite reaching, optimal shareholder returns. The Debt Ratio of 3.83 is below the critical level of 4, indicating that the company is managing its debt levels effectively, marking a strength in its financial structure.

Metric	2025	Met
Revenue Growth (10 Years) *Historical growth ≥ 5%*	5.88	✓
Revenue Growth (3 Years) *Forecasted growth ≥ 5%*	8.58	✓
EBIT Growth (10 Years) *Historical growth ≥ 5%*	2.30	✗
EBIT Growth (3 Years) *Forecasted growth ≥ 5%*	-5.44	✗
EBIT Drawdown *Maximum decline from peak ≤ 30%*	50.15	✗
ROCE *ROCE ≥ 15%*	6.39	✗
ROE *ROE ≥ 15%*	14.07	✗
Debt Ratio *Net Debt/EBITDA < 4*	3.83	✓

Table 1: Overview of historical and forecasted growth metrics and profitability measures

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Profitability Metrics

The company's Gross Profit Margin has shown a positive trend, increasing from 17.23% in 2022 to 21.45% in 2024, indicating improved cost management or pricing power. The EBIT Margin has fluctuated but currently sits at 7.99% in 2024, down from a peak of 12.1% in 2021, signaling potential operational challenges or increased competition impacting profitability. The EBITDA Margin at 14.07% in 2024 reflects a decline from 17.94% in 2021, suggesting that earnings before interest, taxes, depreciation, and amortization have been under pressure. Return on Equity (ROE) has decreased from 22.22% in 2022 to 14.07% in 2024, but remains relatively strong and suggests decent shareholder returns despite the decline. Return on Assets (ROA) remains stable around 4.59% in 2024, down from a high of 7.53% in 2022, indicating a need to improve asset efficiency.

Metric	2021	2022	2023	2024
Gross Profit Margin	19.76	17.23	19.09	21.45
EBIT Margin	12.10	9.84	11.87	7.99
EBITDA Margin	17.94	15.84	17.64	14.07
Return on Equity *ROE ≥ 15%*	18.31	22.22	12.78	14.07
Return on Assets	5.55	7.53	4.54	4.59
Return on Capital Employed *ROCE ≥ 15%*	8.75	8.61	11.28	6.39

Table 2: Key metrics for assessing operational and financial profitability

Liquidity Metrics

The Current Ratio remains stable at approximately 1.1 over the years, suggesting adequate short-term financial health and ability to cover current liabilities. The Quick Ratio, however, is lower at 0.82 in 2024, indicating potential challenges in meeting short-term obligations without selling inventory. The Cash Ratio is low at 0.22 in 2024, emphasizing a limited cash buffer for immediate needs, which could pose liquidity risks. Working Capital has increased from €7.78B in 2022 to €8.7B in 2024, reflecting improved operational liquidity and flexibility.

Metric	2021	2022	2023	2024
Current Ratio	1.13	1.09	1.09	1.10
Quick Ratio	0.92	0.86	0.82	0.82
Cash Ratio	0.21	0.20	0.20	0.22
Working Capital	9,710.00 M €	7,780.00 M €	7,970.00 M €	8,700.00 M €

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Table 3: Liquidity ratios for evaluating short-term solvency

Solvency Metrics

The Debt to Equity ratio is high at 111.63 in 2024, indicating a significant reliance on debt financing, which could pose risks in adverse economic conditions. The Equity Ratio of 35.48% in 2024 shows a moderate level of equity financing, providing a cushion against insolvency. Interest Coverage has decreased dramatically from 97.69 in 2023 to 46.82 in 2024, but remains strong, suggesting the company can comfortably meet its interest obligations. The Net Debt to Equity ratio is 0.89 in 2024, indicating manageable net debt levels relative to equity.

Metric	2021	2022	2023	2024
Debt to Equity	135.21	97.64	97.51	111.63
Equity Ratio	32.73	36.97	37.04	35.48
Interest Coverage	57.02	60.99	97.69	46.82
Net Debt to Equity	1.06	0.74	0.74	0.89

Table 4: Metrics for assessing long-term financial stability

Efficiency Metrics

Asset Turnover has decreased from 0.62 in 2023 to 0.55 in 2024, indicating less efficient use of assets to generate revenue. Receivables Days have increased to 109.14 in 2024, which might suggest slower collection of receivables and potential cash flow issues. Payables Days have increased to 48.55 in 2024, which could indicate extended payment terms with suppliers.

Metric	2021	2022	2023	2024
Asset Turnover	0.50	0.60	0.62	0.55
Receivables Days	129.39	102.73	97.40	109.14
Payables Days	43.19	41.15	45.90	48.55

Table 5: Operational efficiency metrics for evaluating resource utilization

Growth Metrics

Revenue grew from €111.24B in 2021 to €142.38B in 2024, showcasing robust growth. Net Income has declined from €17.94B in 2022 to €7.29B in 2024, raising concerns over profitability. Earnings per Share (EPS) have decreased significantly from €27.31 in 2022 to €11.62 in 2024, reflecting reduced earnings power per share.

Metric	2021	2022	2023	2024

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Revenue	111,240.00 M €	142,610.00 M €	155,500.00 M €	142,380.00 M €
Net Income	12,380.00 M €	17,940.00 M €	11,290.00 M €	7,290.00 M €
Earnings per Share	18.77 €	27.31 €	17.67 €	11.62 €

Table 6: Absolute growth metrics of key financial indicators

Summary

- Revenue Growth is strong both in the long and short term, with 10-year growth at 5.88% and 3-year growth at 8.58%.
- EBIT Growth is a concern, with 10-year growth at 2.30% and 3-year growth at -5.44%.
- Profitability metrics such as Gross Profit Margin have improved, but EBIT and EBITDA margins have declined.
- Liquidity ratios indicate stability in current obligations, but cash reserves are low.
- Solvency is challenged by high debt levels, though interest coverage remains strong.
- Efficiency metrics suggest declining asset utilization and slower receivable collections.
- Despite strong revenue growth, Net Income and EPS have seen significant declines, impacting profitability.

The financial position presents both opportunities and challenges. Strong revenue growth and manageable debt levels are positives, but declining profitability and high debt-to-equity ratios pose risks. The company needs to address EBIT growth and improve operational efficiency to enhance its overall financial health.

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Shareholder Structure

Shareholder Structure Analysis

- The top 10 shareholders hold a significant portion of shares, with the largest shareholder owning just under 10%.
- Institutional investors collectively own [redacted]% of the company, indicating a strong presence of professional investment entities.
- Strategic investors, such as [redacted] and [redacted] own a combined [redacted]%, suggesting a focus on long-term strategic interests.
- The free float is relatively high at [redacted]%, suggesting a wide dispersion of stock ownership among smaller investors.

Top Shareholders

The largest stakeholders of the company and their holdings.

Name	Shares	Percentage (%)	Date	Type
[redacted]	[redacted]	[redacted]	[redacted]	Not Categorized
[redacted]	[redacted]	[redacted]	[redacted]	Not Categorized
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company

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Name	Shares	Percentage (%)	Date	Type
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company
[redacted]	[redacted]	[redacted]	[redacted]	Private Company

Table 7: Overview of key institutional and strategic shareholders of the company

Ownership Structure

Overview of the distribution of company shares by owner type.

Category	Value
Institutional Ownership	[redacted]
Strategic Ownership	[redacted]
Total Number of Shareholders	[redacted]
Free Float (Number of Shares)	[redacted]
Shares Outstanding	[redacted]
Free Float (%)	[redacted]

Table 8: Summary of overall ownership structure and free float percentages

The company's shareholder structure reveals a moderate concentration of ownership among the top 10 shareholders, who collectively hold a substantial portion of the company's equity. The largest shareholders, [redacted] and [redacted], indicate a strategic interest, likely reflecting intentions to influence or stabilize the company's long-term direction and strategic decisions. Institutional investors, such as [redacted], and others, own a significant portion of the shares [redacted]%), which typically ensures a professional level of scrutiny and engagement in corporate governance matters. Their presence can lead to more robust governance practices and a focus on sustainable long-term growth. The high free float of [redacted] highlights a dispersed ownership pattern among smaller retail investors. This dispersion can increase market liquidity but may also lead to less coordinated shareholder actions during critical corporate decisions. The presence of both strategic and institutional investors can provide a balanced approach to governance, combining long-term strategic investments with professional oversight. However, this structure

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could pose risks if strategic interests conflict with those of institutional investors or the broader shareholder base. Overall, this shareholder structure appears to support a stable governance framework while allowing for active market participation. The key risk lies in potential conflicts between strategic and institutional investors, but the benefits include diversified risk and enhanced governance oversight.

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Sustainability Analysis (ESG)

ESG Overall Rating

The ESG score for [redacted] is 90.13 out of 100, with a grade of A. This high score indicates a strong commitment to ESG principles. The overall rating reflects robust performance across all ESG pillars, which is crucial for investors considering sustainable investment opportunities.

ESG Scores

Category	Score	Grade
Total	90.13	A (Excellent)
Environmental	85.63	A+ (Outstanding)
Social	93.31	A (Excellent)
Governance	91.03	B+ (Good)

Table 9: Overview of ESG evaluations with scores and grades in the categories environment, social, and governance

Environmental

The environmental score is 85.63, graded as A+. This score highlights the company's excellent management of environmental issues, demonstrating a strong capacity for sustainability and compliance with environmental standards. The high grade suggests effective measures in reducing carbon emissions and resource usage.

Social

With a social score of 93.31 (Grade: A), [redacted] excels in social responsibility. This score reflects the company's dedication to employee welfare, community engagement, and customer satisfaction. Such a strong social performance is indicative of the company's positive impact on society and its stakeholders.

Governance

The governance score is 91.03, with a B+ grade. This score, while lower than the environmental and social scores, still represents a solid governance framework. It indicates effective board oversight, risk management practices, and transparency in corporate policies.

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Historical Development

Historically, [redacted] maintained an ESG grade of A+. However, there has been a slight downgrade to an A grade currently. This change indicates minor areas where the company might need to enhance its practices to regain its previous standing. The historical chart will provide a visual representation of this development.

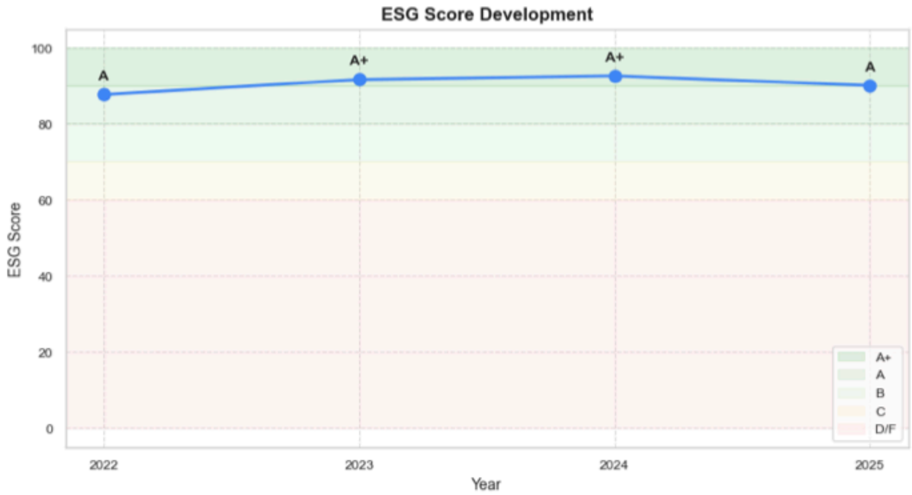

Figure 5: ESG Score Development over time

Risk Assessment

The company's total ESG risk is very low, rated at 0.99 out of 10. Environmental risk is slightly higher at 1.44 but still low, while social and governance risks are even lower at 0.67 and 0.90, respectively. These low risk ratings suggest that the company is well-protected against potential ESG-related challenges.

ESG Risk Assessment

Category	Risk Level	Risk Category
Environmental	1.44	Low
Social	0.67	Low
Governance	0.90	Low
Total	0.99	Low

Table 10: ESG risk assessment with risk level and risk category for environment, social, and governance

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Recommendations

For a risk-seeking investor, [redacted] presents an attractive opportunity to capitalize on its strong ESG performance. The rising trend with a 2.77% change represents potential growth opportunities through further ESG optimization. The company's low-risk profile across all ESG pillars enhances its appeal, providing a solid foundation for sustainable growth investments.

Summary

- [redacted] has a strong overall ESG score of 90.13, graded A.
- Environmental performance is excellent with a score of 85.63 (Grade: A+).
- Social responsibility is a standout feature, scoring 93.31 (Grade: A).
- Governance score is robust at 91.03, though slightly lower at a B+ grade.
- Despite a slight historical downgrade, the company's ESG trend is rising.
- Low ESG-related risks enhance the company's investment attractiveness.

The ESG performance of [redacted] is impressive, particularly for investors seeking growth through sustainability initiatives. The company's low risk and rising trend provide a solid platform for future advancements in ESG practices.

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Sentiment Analysis & Analyst Ratings

Sentiment Analysis Methodology

Sentiment analysis for [redacted] involves retrieving financial news from [redacted] and social media data from [redacted]. This data is then analyzed using the FinBERT model, a specialized BERT model fine-tuned for financial sentiment analysis. The model classifies the sentiment of each piece of content as positive, neutral, or negative.

Sentiment from Financial News and Social Media

In the past 7 days, sentiment from financial news sources reflects a generally neutral to slightly positive outlook for [redacted]:

- Positive News Articles: 121
- Neutral News Articles: 356
- Negative News Articles: 54

The predominance of neutral news articles suggests a stable perception, while the number of positive articles outweighs the negative, indicating a cautiously optimistic sentiment. On Reddit, there were no sentiment data points recorded, which may suggest a lack of significant discussion or interest in the company on this platform over the past week.

7-Day Sentiment

	Positive	Neutral	Negative
News	121	356	54
Reddit	0	0	0

Table 11: 7-Day sentiment analysis with positive, neutral, and negative opinions

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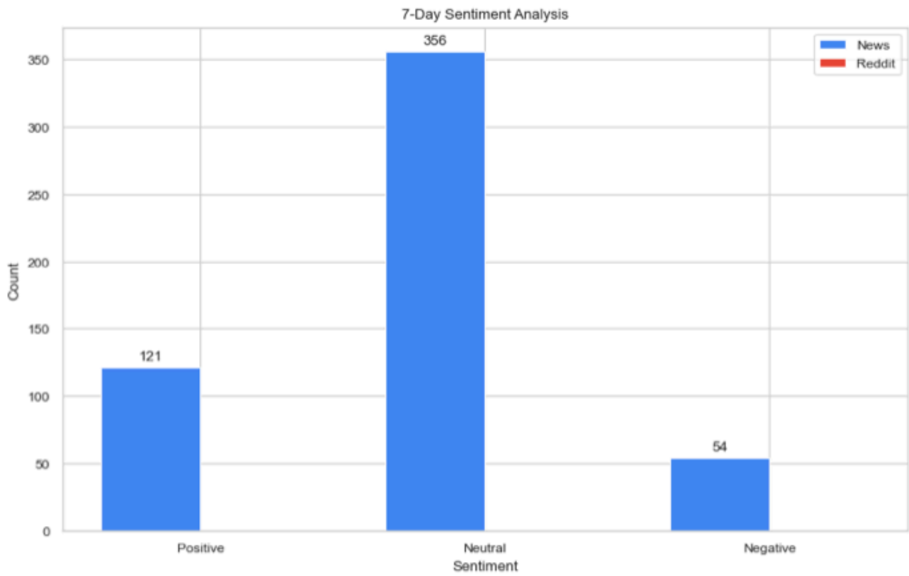

Figure 6: 7-Day Sentiment across platforms

Analyst Ratings

The average analyst rating for [redacted] is "BUY" with a score of 2.4. The distribution of recommendations is as follows:

- Strong Buy: 6
- Buy: 7
- Hold: 9
- Sell: 2
- Strong Sell: 1

The majority of analysts recommend holding or buying the stock, with a minority suggesting selling. This distribution indicates a generally positive outlook among analysts, though with some caution.

Analyst Recommendations

Average Rating: **BUY** (2.40)

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Recommendation Distribution

Strong Buy	Buy	Hold	Sell	Strong Sell
6	7	9	2	1

Table 12: Distribution of analyst recommendations by category

Target Prices

The target price analysis shows:

- Average Target Price: 87.55909 €
- Highest Target Price: 103.0 €
- Lowest Target Price: 68.0 €

These target prices suggest potential for growth from the current market price, with the average target price indicating a moderate upside. The range from the lowest to the highest target price reflects differing views on the company's future performance.

Analyst Target Prices

	€
Average	87.56
Highest	103.00
Lowest	68.00

Table 13: Analyst target prices with average, highest and lowest values

Recommendations

For a risk-neutral investor, the sentiment and analyst ratings for [redacted] suggest a balanced approach. The generally positive sentiment from news and a "BUY" average rating from analysts indicate potential for growth. However, the presence of "Hold" and some "Sell" recommendations advises caution. Investors may consider maintaining or initiating a position, while monitoring market conditions and news for any changes.

Summary

- The sentiment from financial news is predominantly neutral with a positive tilt.
- Analyst ratings are generally favorable with a "BUY" average rating.
- Target prices suggest potential for price appreciation.
- Lack of Reddit sentiment data indicates limited social media discussion.

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Overall, the sentiment and analyst ratings for [redacted] present a cautiously optimistic outlook. Risk-neutral investors may find this an opportune moment to invest, while remaining vigilant for any market changes.

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Risk Analysis

Overview of the Risk Situation for Investors

The current risk landscape for investors involves a combination of high returns and significant volatility. The daily return is 0.3244%, leading to a substantial annual return of 81.76%. However, this is paired with an annual volatility of 30.59%, indicating a high level of price fluctuation. The **Sharpe Ratio** of 0.1657 reflects a modest risk-adjusted return, while the **Sortino Ratio** of 0.5651 suggests a moderate downside risk relative to the expected return. The **Max Drawdown** of -0.0409 highlights the potential for significant losses over a period. Value at Risk (VaR) metrics show potential losses of -2.6947% at the 95% confidence level and -3.7216% at the 99% confidence level, indicating potential short-term financial risks.

Risk Measures

Metric	Value
Daily Return	0.32%
Annual Return	81.76%
Volatility	30.59%
Sharpe Ratio	0.1657
Sortino Ratio	0.5651
Max Drawdown	-4.09%
VaR (95%)	-2.69%
VaR (99%)	-3.72%

Table 14: Overview of risk measures

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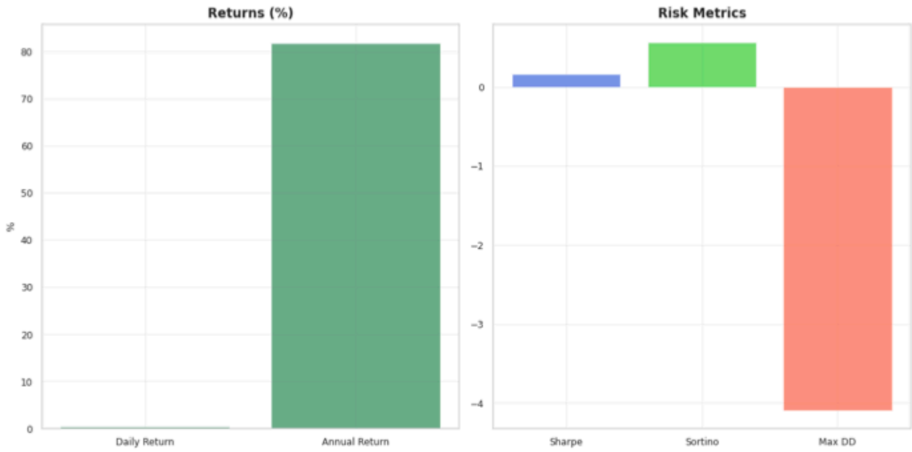

Figure 7: Visualization of return and risk metrics

Recommendations for Investors on How to Deal with the Identified Commodity Dependencies

Commodity Exposure Analysis Methodology: The proprietary analysis method precisely extracts exposure data from the latest annual report using advanced knowledge graph technology and retrieval-augmented generation. Identified commodities are normalized and matched with historical price data. Risk calculation includes correlation and regression analyses between commodity fluctuations and stock price, as well as advanced volatility modeling (GARCH). Hedging effectiveness is quantified by comparing volatility reduction and validated in stress scenarios.

Hedging Analysis

Currency	Exposure (%)
USD	3.20%
CNY	1.50%
GBP	0.60%

Table 15: Currency hedging effectiveness

Commodity	Exposure (%)
Copper	9.00%

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Commodity	Exposure (%)
Aluminium	1.30%
Lithium	1.20%

Table 16: Commodity hedging effectiveness

Category	Effectiveness (%)
Currencies	1.00%
Commodities	3.00%
Overall	2.00%

Table 17: Overall hedging effectiveness

The analysis reveals significant exposure to commodities, with copper being the most influential at 9.00%. This indicates that the stock price is substantially affected by fluctuations in copper prices, making it a critical factor for investors to monitor. Aluminium and lithium also present dependencies, though to a lesser extent. The overall hedging effectiveness is low at 2.00%, suggesting that current strategies may not sufficiently mitigate these risks. Investors should consider diversifying their portfolios to reduce reliance on commodities like copper. This could involve investing in sectors or assets that are less correlated with commodity price movements. Additionally, monitoring global economic indicators that influence commodity prices could provide early warnings of potential risks.

Conclusion and Concrete Action Recommendations for Investors

Investors face a dual challenge of high potential returns and significant risk exposure, particularly due to commodity dependencies. To address these risks: 1. Diversification: Reduce commodity dependency by diversifying into other sectors or asset classes less affected by commodity price fluctuations. 2. Active Monitoring: Keep a close watch on economic indicators and market trends that could impact commodity prices, especially copper. 3. Risk Management Tools: Consider using financial instruments such as commodity futures or options to hedge against adverse price movements in key commodities. 4. Re-evaluation of Hedging Strategies: Given the low overall hedging effectiveness, investors should reassess and potentially enhance their hedging strategies to better protect against commodity price volatility. By taking these actions, investors can better manage the risks associated with commodity dependencies while still capitalizing on the potential high returns.

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Overall Risk Assessment

The overall risk assessment combines various risk metrics into a comprehensive score that represents the risk assessment for the asset.

Introduction to Overall Risk Assessment

The overall risk assessment is a comprehensive evaluation that gauges the potential risk associated with an investment. It is crucial for investors as it helps in understanding the risk-return profile of an investment. With a total score of 45.8 out of 100, the current investment falls into the "Moderate" risk category. This indicates a balanced risk-return relationship, making it suitable for investors seeking a middle ground between risk and reward.

Risk Assessment Methodology

The risk assessment uses a multi-stage calculation approach to evaluate risk across six categories. Each category is assigned a specific weighting, contributing to the overall score:

- **Volatility (25%):** Assesses price fluctuations, including beta and value-at-risk.
- **Volume (15%):** Evaluates trading volume and illiquidity premiums.
- **Performance (25%):** Measures drawdowns and ratios like Sharpe and Sortino.
- **Sentiment (20%):** Analyzes news sentiment and analyst recommendations.
- **ESG (10%):** Considers ESG risks and trend strength.
- **Hedging (5%):** Looks at currency/commodity exposure and hedging effectiveness.

Each score is normalized to a 0-100 scale, with a weighted average calculated to derive the total risk score.

Category Analysis

Here's a detailed analysis of the six risk categories:

- **Volatility (54.8):** Indicates moderate price fluctuations, suggesting potential for gains but also risks of loss.
- **Volume (43.7):** Suggests moderate trading activity, implying a reasonable level of liquidity.
- **Performance (42.5):** Reflects moderate past performance, with some potential for improvement in returns.
- **Sentiment (38.5):** Indicates mixed market sentiment, with potential for sentiment-driven volatility.

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- **ESG (47.3):** Shows a reasonable ESG profile, with room for improvement in environmental, social, and governance practices.
- **Hedging (49.5):** Indicates a moderate level of hedging effectiveness, suggesting some protection against market fluctuations.

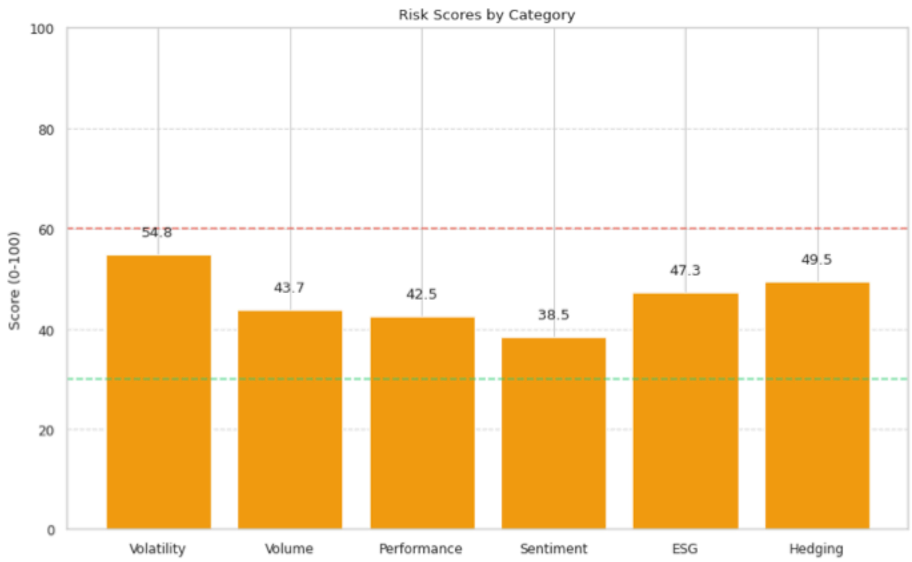

Figure 8: Risk Score by Category

Volatility (54.8)

Measures the price fluctuations of the asset using average volatility, beta, value-at-risk, and volatility profile.

Volume (43.7)

Evaluates the liquidity and tradability of the asset through trading volume, illiquidity premium, and illiquid days.

Performance (42.5)

Considers drawdowns, Sharpe ratio, Sortino ratio, Omega ratio, and debt ratio.

Sentiment (38.5)

Analyzes news sentiment, analyst recommendations, target price spreads, and sell recommendations.

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ESG (47.3)

Evaluates environmental, social, and governance risks, including ESG risk, volatility, change, and trend strength.

Hedging (49.5)

Assesses currency and commodity exposure as well as hedging effectiveness.

Risk Categorization

Risk categories are defined as Low (0-30), Moderate (30-60), and High (60-100). With a score of 45.8, this investment is classified as "Moderate." For investors, especially those with a risk-neutral preference, this implies a balanced approach with potential for both moderate returns and risks, suitable for those who prefer neither extreme risk nor extreme safety.

Recommendations

For risk-neutral investors, the following recommendations are advised:

- Adopt balanced strategies that focus on both risk and return.
- Regularly monitor the investment to ensure alignment with financial goals.
- Address main risk drivers by diversifying across different categories to offset volatility and sentiment risks.
- Consider incrementally increasing exposure in categories with lower risk to optimize the portfolio.

Such strategies can help maintain stability while allowing for growth opportunities.

Summary

The investment's total score of 45.8 places it in the "Moderate" risk category. The main risk drivers include volatility and sentiment, while categories like volume and hedging show lower risk. This profile is generally suited for risk-neutral investors seeking a balanced approach, offering moderate risk and potential returns without extreme exposure.

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Risk Scores

Total Score: 45.8/100

Risk Category: Moderate - Balanced risk profile with potential areas of attention.

Methodology

The overall risk assessment combines six main categories: volatility, volume, performance, sentiment, ESG, and hedging. Each category contains multiple sub-metrics that have been normalized to a 0-100 scale, with higher values representing higher risk. The total score is a weighted average of these categories.

Calculation Methodology

The risk assessment is based on a multi-stage approach:

1. **Data Collection:** Analysis and risk data are loaded from analysis.json and risk_analysis.json and checked for completeness.
2. **Normalization:** All metrics are normalized to a uniform scale of 0-100, with higher values indicating higher risk. For some metrics (e.g., Sharpe Ratio), inverse normalization is applied since lower values represent higher risk.
3. **Category Scores:** The six main categories are calculated as follows:
    - **Volatility (25%):** Average volatility, beta, value-at-risk, and volatility profile
    - **Volume (15%):** Trading volume, illiquidity premium, illiquid days, and volume profile
    - **Performance (25%):** Drawdowns, Sharpe ratio, Sortino ratio, Omega ratio, and debt ratio
    - **Sentiment (20%):** News sentiment, analyst recommendations, target price spreads, and sell recommendations
    - **ESG (10%):** ESG risk, ESG volatility, ESG change, and ESG trend strength
    - **Hedging (5%):** Currency and commodity exposure as well as hedging effectiveness
4. **Risk Type Matching:** The volatility and volume profiles are matched with the investor risk preference to evaluate the alignment between investor and asset.
5. **Total Score:** A weighted average of all category scores, with weights reflecting the relative influence of each category.
6. **Risk Categorization:** The total score is classified into five risk categories: Very low (0-25), Low (25-45), Moderate (45-65), High (65-80), and Very high (80-100).

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Risk Categories

The risk categories are determined based on the total score:

- **Low (0-30)**
- **Moderate (30-60)**
- **High (60-100)**

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DECLARATION ON IDENTITY

I, the undersigned Alexander Maximilian Röser declare that the printed and electronic versions of the doctoral dissertation and thesis booklet are identical in all respects.

Dortmund, 05.03.2026

Alexander Maximilian Röser

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