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

Thesis booklet of the doctoral (PhD) dissertation

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1 PROBLEM STATEMENT, THEORETICAL FRAMEWORK, AND RESEARCH OBJECTIVES

This thesis investigates information asymmetries in single-stock investments through Principal-Agent Theory (PAT), emphasizing the conflict between investors (I) and firms (F) over access to and interpretation of information (Batool et al., 2024; Shah, 2014). Investors often face limited, noisy signals and heterogeneous, bias-prone analyst interpretations, which can distort valuation and lead to inefficient decisions and misallocation of capital (Devos, 2014; Mokoaleli-Mokoteli et al., 2009; Pursiainen, 2022). Despite ongoing digitalization and real-time data availability, a holistic model that integrates diverse data sources with individualized risk preferences remains lacking (Koshiyama et al., 2020; Kruse et al., 2019).

Formally, F knows the "true" company value $V_F = E[\, V \mid I_F \,]$, while I only receives signals, which constitute the investor's information set I_I, and estimates V_I based on them. This implies $V_I = E[\, V \mid I_I \,]$, and in the ex-ante view, $V_F \neq V_I$ is generally expected because I_I does not include all information from I_F. The information asymmetry arises because the investor's information set I_I is a genuine subset of the company's information set I_F, i.e., $I_I \subset I_F$. 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 investor's information set I_I, which is formed from the available signals S, i.e., $P = f(I_I)$, whereby f reflects the investor's interpretation of the signals.

Due to the information asymmetry, the true company value V_F can deviate from the price P, causing a mispricing $\epsilon = V_F - P$. The objective is to minimize the expected absolute deviation between V_F and the investor's estimate produced by a chosen method $\mathcal{M} \in A$ (the set of possible algorithms): $\min_{\mathcal{M} \in A} E\left[|V_F - V_I(\mathcal{M})|\right]$. The aim of the thesis is to minimize the information asymmetry ΔI by means of an AI-based Decision Support System (AI-DSS).

Timeliness derives from the continuing importance of information asymmetries for retail and institutional investors, their potential to impair decision efficiency and increase mispricing risk, and the feasibility of multi-source analytics in modern markets (Shah, 2014; Koshiyama et al., 2020; Kruse et al., 2019). Practical relevance is reinforced by regulatory requirements under Markets in Financial Instruments Directive II (MiFID II), which mandate assessing investor suitability and risk profiles (Gortsos, 2018; Kümmerle & Conen, 2018).

The objectives of the AI-DSS are as follows:

- Determination of investor risk preferences: Identify risk preferences in line with MiFID II using standardized questions, enabling compliant, personalized analysis.
- Analysis of specific stocks: Focus the analysis on a selected single stock via ISIN, ensuring relevance and scope control.
- Generate tailored investment reports: Synthesize fundamental, technical, and sentiment data from APIs, web scraping,

machine learning, and generative AI into clear, actionable insights aligned with the investor's risk profile.

- Enhance decision-making by reducing information asymmetries: Provide transparent, risk-adjusted communication that minimizes discrepancies between perceived and true company values.

2 RESEARCH QUESTIONS, HYPOTHESIS, AND METHODOLOGICAL DESIGN

This thesis adopts a theory-driven, deductive, non-experimental empirical field design that collects longitudinal data at multiple points in time (Dinh et al., 2022; Döring, 2023; Pfaffenberger, 2016). It is grounded in PAT (Jensen & Meckling, 1976; Ross, 1973), which defines the problem of information asymmetries in financial markets and motivates the use of primarily collected data, while allowing for secondary analyses in an open science context.

The research questions (RQ) are specified exactly as in the input:

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

The following hypothesis formalizes RQ1/RQ2:

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

This AI-DSS research project aims to reduce information asymmetries and assist individual investment decisions by addressing two specific research questions and a focused hypothesis. Following established

DSR methodology, which prioritizes problem relevance, artefact development, and rigorous evaluation over hypothesis quantity (Elragal & Haddara, 2019; Hevner, 2007; Kotzé et al., 2015), the structure is sound. Earlier studies indicate that some DSR projects do not include formal hypotheses at all (Hoang et al., 2019). Therefore, this thesis adopts a focused strategy with two research questions and one hypothesis.

Regarding the methodology, this thesis adopts the DSR approach, as illustrated in Figure 1. Within a DSR methodology, the project is structured into a single design and development phase followed by a two-part evaluation, forming a coherent artifact-centric inquiry.

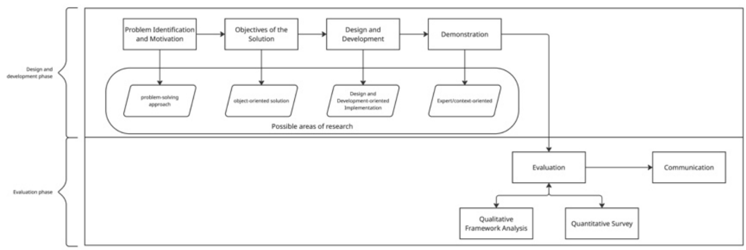

Figure 1: Illustration of the DSR process

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

For transparent communication, the project is presented as a DSR grid (Table 1) summarizing problem description, input knowledge (Ω-knowledge; λ-knowledge), research process, key concepts, solution description, and output knowledge (Gregor & Hevner, 2013; Venable et al., 2019, 2019).

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

Element	Description
Problem Description (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; Jensen & Meckling, 1976; Ross, 1973; Shah, 2014) . λ-Knowledge**:** Existing AI and data science models and web scraping technologies (Araci, 2019; Bartelt & Röser, 2024a, 2024b; 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).

Element	Description
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 (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 collectively encompass all six DSR stages (Peffers et al., 2007) integrating problem identification, objective definition, artifact design and development, and demonstration, evaluation, and communication in a focused single-iteration process (see also Figure 1).

The methodology comprises two principal components: first, the design and development phase, and second, the evaluation phase.

The design and development phase constructs the AI-DSS in a single build iteration, drawing on established quantitative methods such as ARIMA, GARCH/EGARCH, and NLP, with design objectives refined through feedback from industry leaders (Hevner et al., 2004).

The artifact follows a four-layer architecture (λ-Knowledge, see Figure 1) consisting of input, data analysis, scoring, and output layers. Investor risk preferences are collected in line with MiFID II via standardized questionnaires, while market data (fundamental, technical, and sentiment) are aggregated through APIs and web scraping sources (e.g., Reddit, LSEG). Volatility is modeled via GARCH/EGARCH, and textual information is processed using NLP; generative AI supports synthesis and explanation. The resulting reports emphasize transparency and risk-adjusted alignment with individual investor profiles, ensuring professional comparability and interpretability.

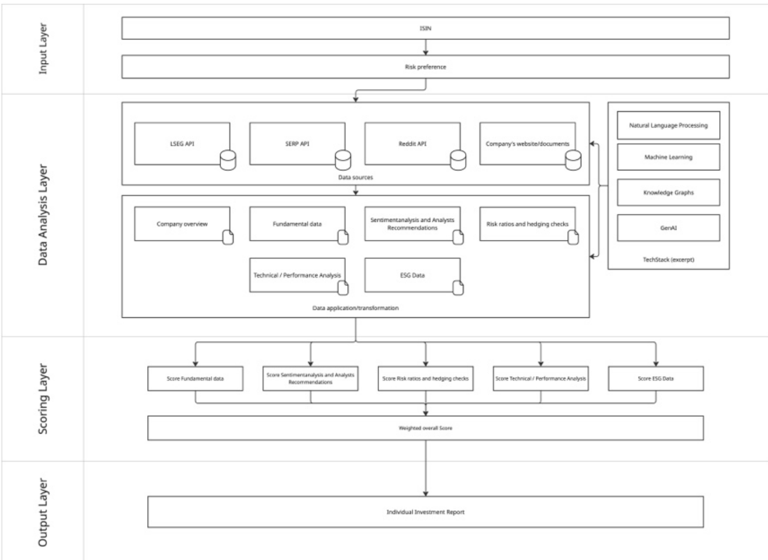

Figure 1: Development design of the AI-DSS

Source: own elaboration

The standard evaluation process was modified to include four evaluation stages. Eval 1 addresses problem identification, while Eval 2 covers solution design. Evaluations of Eval 1 and Eval 2 are deliberately omitted: PAT provides a well-established conceptualization of the information asymmetry problem (Eisenhardt, 1989; Jensen & Meckling, 1976; Ross, 1973; Shah, 2014), and the AI-DSS design builds upon validated, state-of-the-art analytical and AI methods, rendering separate testing of these stages unnecessary. The subsequent phases, Eval 3 (solution instantiation) and Eval 4 (solution in use), were extensively assessed through a methodological triangulation approach organized into two complementary components aligned with DSR principles. This approach maintains methodological rigor and employs a single-iteration process that systematically examines the research questions and hypothesis.

A framework analysis addresses the central research questions (RQ1 & RQ2), while a quantitative questionnaire tests the hypothesis (H), focusing on Eval 3 (solution instantiation) and Eval 4 (solution in use) (Sonnenberg & Vom Brocke, 2012).

The evaluation process involves benchmarking against 11 professional reports and conducting a questionnaire of 18 experts who assess the criteria of transparency, risk adjustment, relevance, and efficiency. The DSR principles of relevance, rigor, transparency, validity, and reliability (Peffers et al., 2007), along with MiFID II suitability guidelines, were applied.

3 RESULTS OF THE EMPIRICAL EVALUATION

The evaluation applies a methodological triangulation approach, combining a qualitative framework analysis with a quantitative expert questionnaire to assess how the AI-DSS supports risk-based investment decisions (Denzin, 2017; Flick, 2011; Peffers et al., 2007; Sonnenberg & Vom Brocke, 2012; Venable et al., 2019). The assessments are conducted using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Consequently, a score of 5 indicates complete (100%) agreement within the context of either the framework analysis or the expert questionnaire.

3.1 Framework Analysis

n the framework analysis, the AI-DSS report is applied to a specifically selected company that strategically operates both as a manufacturer and a trading firm - the renowned automobile producer Mercedes-Benz Group AG. It is compared against eleven anonymized analyst reports across four deductively defined categories: *transparency*; *adjustment to risk willingness*; *relevance* and *completeness*; and *efficiency and practicability*. The AI-DSS consistently outperforms the benchmark set.

In *transparency* (three criteria, each weighted 10%), peer reports average about 2.6 out of 5 (individual averages 2.3–3.3) with moderate-to-high variability (e.g., SD of 1.4 for recommendation comprehensibility; Report 9 scored 5), whereas the AI-DSS averages 4.3 out of 5, a difference of +1.7, with notably stronger disclosure of risks and uncertainties.

In *adjustment to risk willingness* (three criteria, each 10%), peer reports uniformly score 1.0 out of 5 (no variance), while the AI-DSS averages 3.7 out of 5 (+2.7), evidencing customization and flexibility for distinct risk profiles that conventional reports do not provide.

In *relevance and completeness* (two criteria at 10%, one at 5%), peer reports average about 2.8 out of 5 (range 2.5–3.1; e.g., Report 9 up to 4; Report 11 between 1 and 2 out of 5), whereas the AI-DSS achieves 4.7 out of 5 (+1.9), with stronger completeness and decision relevance and less distinction in data integration but still favorable.

In *efficiency and practicability* (10% and 5%), peer reports average approximately 2.85 out of 5 with considerable variation, while the AI-DSS consistently scores 5.0 out of 5, indicating superior usability and practical utility; although Reports 8 and 9 show relatively higher scores within the peer set, they do not match the overall practicality of the AI-DSS.

Overall, peer reports range from 1.25 to 3.30 out of 5 (mean 2.22), while the AI-DSS scores 4.35 out of 5 (+2.13). Traditional reports are consistently weakest in risk adjustment and vary in transparency and efficiency; even the best peer (Report 9) nears the AI-DSS in relevance but falls short overall. These results substantively support the hypothesis by showing that the artifact mitigates information asymmetries through completeness, customization, and practicality.

3.2 Quantitative Questionnaire

The quantitative questionnaire evaluates the AI-DSS report via expert ratings from N=18 validated financial professionals using 5-point Likert scales across three dimensions: *content quality*, *reduction of information asymmetries*, and *efficiency/practical usability*.

The expert panel's demographic profile supports the validity of the assessment, with balanced experience (one <2 years; seven 2–5 years; three 6–10 years; seven >10 years), varied engagement with analyst reports (nine occasionally, four regularly, five frequently), diverse analytical self-assessment (seven basic, seven advanced, four expert), and practical involvement in investment decisions (one never; eight occasionally; four regularly; five frequently).

Bootstrap resampling (B=1,000 and B=2,000; percentile and BCa) yields 100% confidence interval overlap across methods and iterations, with relative CI widths of 0.149–0.188 and small observed–bootstrap deviations (e.g., 0.004/0.003; 0.006/0.002), indicating high precision and stability. Reliability is strong across scales (Cronbach's alpha 0.760–0.837), with ordinal measures based on polychoric correlations reaching up to 0.915 for alpha and omega.

In *content quality* (8 items), observed means range from 3.83 to 4.33 out of 5, with an overall profile at approximately 4.11 out of 5. The *shareholder structure analysis* is highest (M=4.33, 95% CI [3.98, 4.69]), while *stock price analysis* is lowest yet positive (M=3.83, [3.47, 4.20]); internal consistency is excellent (alpha=0.837; corrected item–total correlations exceed minimum thresholds; ordinal alpha/omega 0.915/0.915).

In *reducing information asymmetries* (4 items), means range from 3.72 to 4.39 out of 5 (overall ≈4.05), led by increased transparency on financials, risks, and market position (M=4.39, [4.07, 4.71]); tailored information by risk willingness is lowest (M=3.72, [3.37, 4.07]), indicating scope for deeper personalization; reliability is acceptable (alpha=0.760; ordinal alpha/omega 0.838/0.845).

In *efficiency and practical usability* (4 items), means range from 3.94 to 4.17 out of 5 (overall ≈4.03), led by faster decision-making (M=4.17, [3.88, 4.45]); time savings versus manual analysis is lowest (M=3.94, [3.46, 4.43]); reliability is acceptable (alpha=0.767, with wider CIs typical for k=4; ordinal alpha/omega 0.823/0.837), and alpha-if-item-deleted shows only marginal gains if *time savings* or *efficiency* were removed.

Across both analyses, the framework analysis and the quantitative questionnaire, the results indicate similar patterns between the framework evaluation and the expert questionnaire. The AI-DSS recorded higher average scores than all benchmark reports and in the quantitative questionnaire for each evaluated category. The overall results across both methodological approaches indicate stable measurement outcomes with high internal consistency and narrow confidence intervals. These findings provide a consolidated overview of the empirical evaluation and form the basis for the subsequent conclusion.

4 CONCLUSION

Information asymmetry between investors and companies shapes single-stock investment decisions, as explained by theories like PAT. This thesis explores how an AI-DSS can help reduce such asymmetries. Demonstration and evaluation highlight the significant impact of an AI-DSS on these decisions. The study answers two main research questions (RQ1 and RQ2) and tests one hypothesis, all assessed via methodological triangulation. Evaluation covered usability and robustness (Eval 3), effectiveness and practicability (Eval 4), along with initial problem identification (Eval 1) and solution design (Eval 2). Detailed responses to RQ1 and RQ2 follow, supporting the hypothesis; key evaluation points are *italicized*.

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

Within the framework analysis, *adjustments to risk willingness* are divided into three criteria: *consideration of risk profiles*, *individualized decision support*, and *flexibility*. The AI-DSS report outperformed 11 traditional investment reports, scoring 4 out of 5 on risk *profile and individualized support* (versus 1 out of 5 for traditional reports), and 3 out of 5 on *flexibility* (traditional reports scored 1 out of 5). Overall, traditional reports often overlook these factors, while AI-DSS supports more personalized, flexible decisions.

An expert questionnaire (N=18) strongly supports the research question, showing that the AI-DSS report provides *useful, risk-based investment guidance*. This statement under review averages 3.72 out of 5 (trimmed mean: 3.75), with robust confidence intervals ([3.33, 4.00] BCa-CI; [3.38, 4.06] trimmed CI). Scale reliability is solid (α=0.760; CITC: 0.486 Pearson, 0.532 polychoric).

The *recommended investor actions, tailored to different risk profiles*, scored an average of 4.0 out of 5 and demonstrated strong reliability (α=0.767; CITC: 0.805 Pearson, 0.935 polychoric), with bootstrapped CIs above negative thresholds. The report is relevant for analyses like *stock price* (mean: 3.83, CITC: 0.473), *shareholder structure* (mean: 4.33, CITC: 0.521), and *fundamental data* (mean: 4.28, CITC: 0.697), each with stable, positive evaluations and internal consistency.

The results show that the AI-DSS demonstrates strong analytical support for investor profiles, with consistently reliable item characteristics. Both percentile and BCa bootstrap methods yield similar, stable estimates, minimal deviation between observed values and bootstrap means (≈ 0.000–0.005), and complete CI overlap between resampling sizes. Reliability analyses (Cronbach's α) and ordinal reliability coefficients, along with Omega values, indicate excellent internal consistency and robustness of the scales, confirming the model's reliability for evaluating the AI-DSS's analytical quality.

In summary, RQ1 is positively answered: the AI-DSS personalizes investment reports to individual risk preferences and enables evidence-based decisions. Results show that it offers adaptive analyses, reduces bias, and provides greater personalization than typical reports. The system also reliably aids single-stock decisions within each investor's risk willingness.

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

The AI-DSS leverages diverse data sources and algorithms - such as EGARCH for volatility, NLP for sentiment, pandas for processing, and LLMs for context - to produce individual investment reports. Evaluation shows these reports excel at delivering tailored information and reducing information gaps due to the system's robust architecture.

The framework analysis covers four topics related to RQ2: *completeness*, *integration of diverse data*, *risk disclosure*, and *clarity*. AI-DSS reports scored higher than traditional investment reports across all categories, with 5 out of 5 for *completeness and relevance* (versus 2.82 and 2.55), 4 out of 5 for *integrating heterogenous data* (versus 3.09), and 5 out of 5 for *risk disclosure* (versus 2.36). The AI-DSS also scored better in *risk profile consideration* (4 out of 5 vs. 1.00) and *clarity* (4 out of 5 vs. 3.27), largely due to its advanced algorithms, including EGARCH and NLP models. Overall, AI-DSS outperforms traditional reports in personalization and transparency, helping reduce information asymmetries.

The expert questionnaire (N=18) and framework analysis support robust findings for RQ2. The AI-DSS report *delivers tailored information based on investor risk preferences*, with a mean score of 3.72 out of 5 (10% trimmed mean: 3.75), demonstrating minimal bias and reliable positive evaluation (95% BCa-CI: [3.33, 4.00]). *Combining various analyses* (e.g., stock price, ESG, fundamentals) *presents a comprehensive view that reduces information asymmetries*, scoring 4.28 out of 5 (95% BCa-CI: [4.00, 4.50]). The report also *improves transparency on financials, risks, and market positioning* (mean: 4.39). It *addresses uncertainties* (such as profitability declines and volatility) to enhance investor confidence, reflected in a 3.83 out of 5 score. *Stock price analysis* leveraging models like EGARCH scores 3.83/5, *sentiment analysis and analyst ratings* using NLP reach 4.17, *fundamental data assessments* score 4.28, and ESG contextualization via LLMs achieves 4.17. Across items, high CITC and Cronbach's alpha values indicate strong reliability in reducing information asymmetries and delivering customized insights.

Questionnaire results support previous findings: experts rated content quality at 4.11 out of 5 and holistic views at 4.28/5, with efficiency and utility around 4.03 out of 5 ($\alpha = 0.767$–0.837; confidence intervals overlapped). These results highlight the DSR triangulation method's rigor, combining structured matrices and bootstrapped results. RQ2 is validated - AI-DSS components reduce information asymmetries and provide tailored security data. Consistent results from RQ1 and RQ2 enable empirical testing of AI-based DSS significant minimizations on information asymmetry.

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 effectively reduces information asymmetries between firms and investors through targeted data analysis. In framework analyses, *transparency* and *relevance/completeness* criteria were strongly met by AI-DSS reports (scoring 4–5 out of 5), surpassing traditional reports, which scored lower across all metrics. Notably, the AI-DSS excelled in *clarity*, *risk disclosure*, and *integrating diverse data sources*.

Questionnaire results (N=18) further support these findings: the AI-DSS was rated highly (mean scores 3.72–4.44) for *enhancing transparency about a company's financial condition*, *addressing uncertainties*, and *providing tailored information* to help investors make informed decisions. *Combining various analyses* (e.g., stock price, ESG, fundamentals) was seen as especially effective in reducing information gaps. Additional items indicated that the AI-DSS offered *transparent*, *comprehensive company overviews* and *accessible risk analyses*, further *supporting its role in mitigating asymmetries*.

Reliability analyses confirmed strong measurement consistency (Cronbach's α = 0.760, Ω = 0.845), and bootstrapping demonstrated stable estimation (minimal deviations, high CI overlap). Overall, empirical evidence robustly supports the hypothesis that AI-based DSS can minimize discrepancies between firm value and investor-perceived value via focused data analysis, with results remaining consistently positive across analytical dimensions.

In summary, the findings confirm that the AI-DSS offers a reliable, empirically supported framework for improving single-stock investment decisions. Its adaptive analytics and modular design personalize recommendations based on investor risk profiles and reduce information gaps through transparent, data-driven methods. Both qualitative and quantitative evaluations highlight its methodological strength and practical value. Integrating AI techniques - such as volatility modeling, sentiment analysis, and large language models - improves personalization, reliability, and interpretability of investment recommendations.

New Scientific Results

On the basis of the validated answers to RQ1 and RQ2 and the empirical support for the hypothesis, the central scientific contributions of this dissertation can be condensed into the following new scientific results.

I. Investor risk preferences can be systematically operationalized within an AI-driven decision support architecture, constituting an advancement over conventional analyst reports by addressing deficiencies in transparency, risk personalization, and analytical integration.

II. A multi-layered architecture integrating heterogeneous financial, technical, and sentiment data with quantitative and qualitative methods forms a coherent AI-based decision support system.

III. The integrated analytical framework demonstrably enhances transparency, risk alignment, completeness, and practical usability compared to traditional investment reports.

IV. Methodological triangulation provides convergent empirical evidence for the robustness and internal consistency of the approach.

V. The dissertation contributes validated design knowledge for integrating heterogeneous data, multi-method analytics, and risk-based personalization within Design Science Research for financial AI-DSS.

5 RECOMMENDATIONS

Future research should broaden the scope of AI-DSSs in financial markets. Longitudinal studies can assess how AI-DSSs influence portfolio adjustments and investor risk profiles over time. Personalization, such as allowing users to upload their portfolios, helps evaluating individual risk and optimize recommendations. Incorporating ETF look-through analyses and peer group comparisons can enhance diversification assessments and benchmarking.

Methodologically, integrating reinforcement learning and explainable AI can improve transparency, adaptability, and user trust. Ethical and regulatory issues - like fairness, explainability, and compliance with frameworks such as the EU AI Act - should remain a priority to ensure responsible deployment.

In summary, combining AI with human judgment through advanced AI-DSS offers more transparent and evidence-based financial services, reduces biases, and supports financial innovation and investor empowerment.

6 AUTHORS SCIENTIFIC PUBLICATIONS RELATED TO THE TOPIC OF THE DISSERTATION

Author(s)	Title	DOI/ISBN	Status
Bartelt, C., & Röser, A. M.	*AI in finance: Innovative approaches for sustainable business models.*	https://doi.org/10.17836/EC.2024.2.007	published
Bartelt, C., & Röser, A. M.	*Transforming the operational components of marketing processes with GenAI: A paradigm shift.*	https://doi.org/10.54364/AAIML.2024.43148	published
Bartelt, C., & Röser, A. M.	*Artificial intelligence as a catalyst for sustainable business innovation: Perspectives from finance and marketing.*	https://doi.org/10.21637/GT.2024.2.02	published
Röser, A. M., & Bartelt, C.	*A generative AI and neural network approach to sustainable digital transformation: A focus on medical and marketing sectors.*	https://doi.org/10.35511/978-963-334-499-6-Roser-Bartelt	published
Röser, A. M., & Englert, R. A.	*Experimental indication to improve the NN learning accuracy by integrity constraints from the NN training data.*	https://doi.org/10.54364/AAIML.2024.42134	published
Röser, A. M.	*Anwendung von neuronalen Netzen zur Evaluierung des Aktienindex auf Basis von Aktienverläufen und Zinsniveau.*	978-3-89275-363-6	published
Hildenbrand, T., Röser, A. M., & Zureck, A.	*The impact of ESG ratings on the systematic and unsystematic risk of European companies.*	tbc	accepted for publication
Akbay, S., & Röser, A. M.	*The impact of ESG scores on company value and market capitalization volatility: An empirical analysis.*	tbc	accepted for publication
Weiß, R., Röser, A. M., & Zureck, A.	*AI in financial reporting: Streamlining risk management and ESG compliance in Europe.* In *The rise of AI agents.*	tbc	accepted for publication
Röser, A. M., & Englert, R. A.	*Experimental analysis of the NNIC approach to improve learning results for NN.*	tbc	under review

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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.

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