Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 79-96
Publication Link: https://jmi.stekom.ac.id/index.php/jmi/issue/view/14

Scenario Simulation of Ethical Trade-Offs in Executive Financial Strategy

Issabell Zhang*[1], Christina Tan[1]
Email: issabell895@gmail.com
[1,2]*Business Analytics and Accounting, University of Rochester, NY, USA*
*Corresponding Author

Abstract

The integration of artificial intelligence into executive financial decision-making has introduced new ethical challenges, creating complex trade-offs between financial optimality and ethical considerations. Current methodologies remain inadequate for systematically quantifying these dilemmas in strategic financial contexts. This study introduces a novel scenario-based simulation framework to measure and analyze trade-offs between financial performance and ethical consequences in AI-augmented decision environments. The research employs computational simulation modeling across ten strategic financial scenarios, involving configured AI agents and behaviorally profiled human agents executing 1,000 iterations per scenario under controlled conditions. The results indicate that ethical trade-offs are highly context-dependent, with 40% of scenarios showing a statistically significant negative correlation between financial and ethical outcomes. In high-conflict scenarios, AI-driven ethical considerations improve ethical scores by 34% while incurring an 18% opportunity cost in financial performance. Executive behavioral biases, particularly overconfidence and loss aversion, significantly degrade ethical outcomes beyond the improvements achieved through AI ethical calibration. Methodologically, this study contributes a replicable and extensible simulation-based approach for systematically quantifying ethical–financial trade-offs under controlled yet behaviorally grounded conditions. Practically, the findings provide actionable managerial and governance implications by informing the design of ethical audit mechanisms, bias mitigation strategies, and AI calibration policies in financial decision-making. The framework enables executives and regulators to conduct proactive ethical audits of AI systems, bridging the gap between theoretical AI ethics and practical financial governance.

Keywords: *Ethical Decision-Making, AI Governance, Behavioral Finance, Scenario Simulation, Executive Financial Strategy.*

Received in March 2026; Revised in June 2026; Accepted in July 2026; Published in August 2026.

I. INTRODUCTION

The growing integration of AI into business financial planning represents a critical paradigm shift in contemporary finance. Sophisticated algorithms are increasingly used to support high-stakes decisions such as mergers and acquisitions, capital allocation, and risk management. According to (Narne et al., 2023; Oktavia & Wibowo, 2025; Owusu-Mensah et al., 2025), these technologies not only enhance analytical depth but also improve operational efficiency. However, this transformation also introduces complex ethical considerations that extend far beyond traditional financial evaluation. In particular, AI-driven optimization may prioritize financial gains while simultaneously generating significant societal externalities, thereby intensifying ethical tensions in executive decision-making contexts. According to (Jones, 2023; Lehner et al., 2022; Roberts et al., 2024), such tensions are becoming increasingly salient in AI-assisted financial strategies.

Contemporary studies reveal a substantial gap between theoretical discussions of AI ethics and their practical implementation in financial decision-making. While accountability mechanisms have been explored in corporate governance literature (Christianah Pelumi Efunniyi et al., 2024;

DOI: https://doi.org/10.51903/jmi.v5i2.319

Dell'Erba & Gomtsyan, 2024; Yue et al., 2025), and behavioral finance has documented pervasive cognitive biases such as overconfidence and loss aversion (Almansour et al., 2023; Maulida & Permata Sari, 2023; Meisa Dai et al., 2021; Risman et al., 2023), these streams are rarely integrated into actionable managerial frameworks. As a result, organizations lack rigorous tools to evaluate the ethical implications of AI-driven recommendations prior to implementation. This gap creates governance vulnerabilities with potentially severe consequences, as highlighted by (Batool et al., 2025; Birkstedt et al., 2023; Mäntymäki et al., 2022; Taeihagh, 2025). Addressing this limitation requires approaches that can simultaneously operationalize ethical constructs and empirically evaluate their interaction with financial outcomes in AI-supported environments.

The scenario-based simulation approach offers distinct advantages for addressing these challenges, particularly by enabling controlled experimentation without real-world risks (Rachmawati et al., 2023; Şentürk Erenel et al., 2020; Svellingen et al., 2021; Zheng et al., 2024). Predictive simulations allow for the identification of systematic patterns in how AI configurations and executive behavioral profiles influence decision outcomes across varying contexts. These patterns can reveal how financial and ethical priorities are dynamically balanced or conflicted in automated decision-making processes. Building on this premise, this study develops a structured simulation framework that captures both AI-driven optimization logic and human behavioral biases within unified experimental settings. This study contributes in two ways: methodologically, it introduces a simulation-based framework that translates abstract ethical principles in AI governance into quantifiable variables suitable for financial modeling; empirically, it demonstrates how ethical–financial trade-offs emerge across scenarios, showing context-dependent conflicts and measurable impacts of AI calibration and executive biases on decision outcomes. Methodological contribution lies in the design of a replicable and extensible simulation architecture, while empirical findings show that trade-offs between ethical and financial performance are not only measurable but systematically influenced by scenario conditions and behavioral factors. Figure 1 encapsulates the conceptual framework underlying this study.

II. LITERATURE REVIEW

A. Ethical Foundations of Financial Decision-Making

Theory of ethical decision-making encompasses a wide array of normative principles proposed to define ethical decision-making models. Classical models defined the process of ethical decision-making on a linear procedure involving stages of moral perception, forming a decision, determining intentions, and finally, action (Osasona, Oladipupo Amoo, et al., 2024; Pembi & Ali, 2024). In finance, it becomes more complex due to organizational influences, ambiguous motives, and information asymmetry. Nevertheless, more contemporary literature has argued that ethical decision-making in finance is not binary but represents a dynamic conflict between competing interests (Osasona, Oladipupo Amoo, et al., 2024; Rodgers et al., 2023; Tolmeijer et al., 2022). This dynamic perspective is particularly relevant for AI governance, where ethical evaluation must be continuously negotiated rather than statically defined, requiring decision frameworks that can adapt to evolving financial and societal priorities. The integration of AI technology further complicates this landscape by blurring responsibility between human judgment and algorithmic recommendations. From a managerial standpoint, this implies that executives must move beyond static ethical checklists toward more flexible and context-sensitive evaluation mechanisms in AI-supported financial environments.

B. Behavioral Finance and Executive Psychology

Research in behavioral finance has revealed cognitive biases and heuristics that undermine traditional assumptions of rational decision-making. Key biases such as overconfidence, loss aversion, and herd behavior distort risk perception and valuation, often leading to suboptimal financial outcomes (Almansour et al., 2023; Risman et al., 2023; Wu et al., 2022). These biases become even more critical in AI-supported contexts, where human judgment interacts with algorithmic outputs. Empirical studies show that overconfidence may lead executives to disregard AI-generated risk warnings, while loss aversion can increase dependence on automated recommendations during uncertainty (Wu et al., 2022). Such interactions highlight the need for AI governance frameworks that explicitly incorporate behavioral risk factors rather than assuming neutral human oversight. Managerially, this underscores the importance of designing decision support systems and governance protocols that actively mitigate bias amplification in human–AI collaboration. The persistence of these biases reinforces the importance of embedding behavioral insights into AI governance models.

C. AI Governance and Responsible Innovation

The emerging field of AI governance introduces principles and mechanisms aimed at ensuring accountability in algorithmic decision-making. Systematic reviews emphasize core principles such as transparency, fairness, accountability, and human oversight across various domains. In financial contexts, these translate into requirements for explainable credit scoring models, auditable trading algorithms, and accountable AI-supported strategic planning. However, practical implementation remains limited, often involving trade-offs between competing objectives such as predictive accuracy and fairness, or efficiency and transparency (Ayana et al., 2024; Hadfield & Anthropic, 2023; Roberts et al., 2024). These trade-offs are inherently managerial in nature, requiring decision-makers to balance regulatory compliance, ethical responsibility, and performance objectives within constrained organizational settings. Therefore, AI governance is not merely a technical or regulatory concern but a strategic managerial function that demands tools capable of operationalizing and evaluating these competing priorities. This highlights the need for practical frameworks that can systematically articulate and assess such trade-offs in real-world applications.

D. Simulation Methodologies in Complex Systems

Scenario-based simulations have proven to be effective tools for analyzing complex decision environments. Prior studies have applied simulation techniques to domains such as supply chain optimization, healthcare training, and environmental management (Arora et al., 2021; Elendu et al., 2024; Romano Alho et al., 2021; Tao et al., 2022; Zhong et al., 2021). These approaches enable controlled experimentation by isolating variables and testing strategic responses without real-world risks. In management research, simulations provide a structured way to analyze decision dynamics under varying conditions (Rachmawati et al., 2023). More recent developments incorporate agent-based modeling and machine learning to simulate interactions between human and AI agents (Chai et al., 2023; Zheng et al., 2024). This methodological evolution is highly relevant for AI governance, as it enables the testing of ethical and behavioral scenarios in controlled environments before real-world deployment. From a managerial perspective, simulation tools offer a practical mechanism for stress-testing governance strategies, evaluating policy interventions, and anticipating unintended consequences in AI-driven financial decision-making. This provides a strong methodological foundation for developing frameworks that address ethical dimensions in AI-augmented contexts.

Table 1. Theoretical Foundations and Research Gaps

Theoretical Domain	Key Concepts	Representative Studies	Identified Gaps
Ethical Decision-Making	Moral reasoning stages, stakeholder theory, normative frameworks	(Osasona, Oladipupo Amoo, et al., 2024; Pembi & Ali, 2024)	Limited quantification of ethical trade-offs in AI contexts
Behavioral Finance	Cognitive biases, risk perception, heuristics	(Almansour et al., 2023; Risman et al., 2023; Wu et al., 2022)	Insufficient integration with AI interaction dynamics
AI Governance	Transparency, accountability, fairness principles	(Batool et al., 2025; Birkstedt et al., 2023; Lu et al., 2024)	Implementation challenges in financial decision contexts
Simulation Methodology	Scenario analysis, agent-based modeling, computational experiments	(Arora et al., 2021; Rachmawati et al., 2023; Tao et al., 2022)	Limited application to ethical dimensions in finance

Table 1 synthesizes these theoretical foundations and identifies the critical research gaps that this study intends to address. The table also illustrates how the extant literature, while robust within individual domains, rarely adopts integrative approaches that simultaneously consider ethical, behavioral, and technological dimensions in financial decision contexts. Importantly, this fragmentation limits the ability of organizations to translate theoretical insights into actionable AI governance practices. Bridging these domains is therefore essential not only for academic advancement but also for enabling more effective managerial decision-making in AI-supported financial environments.

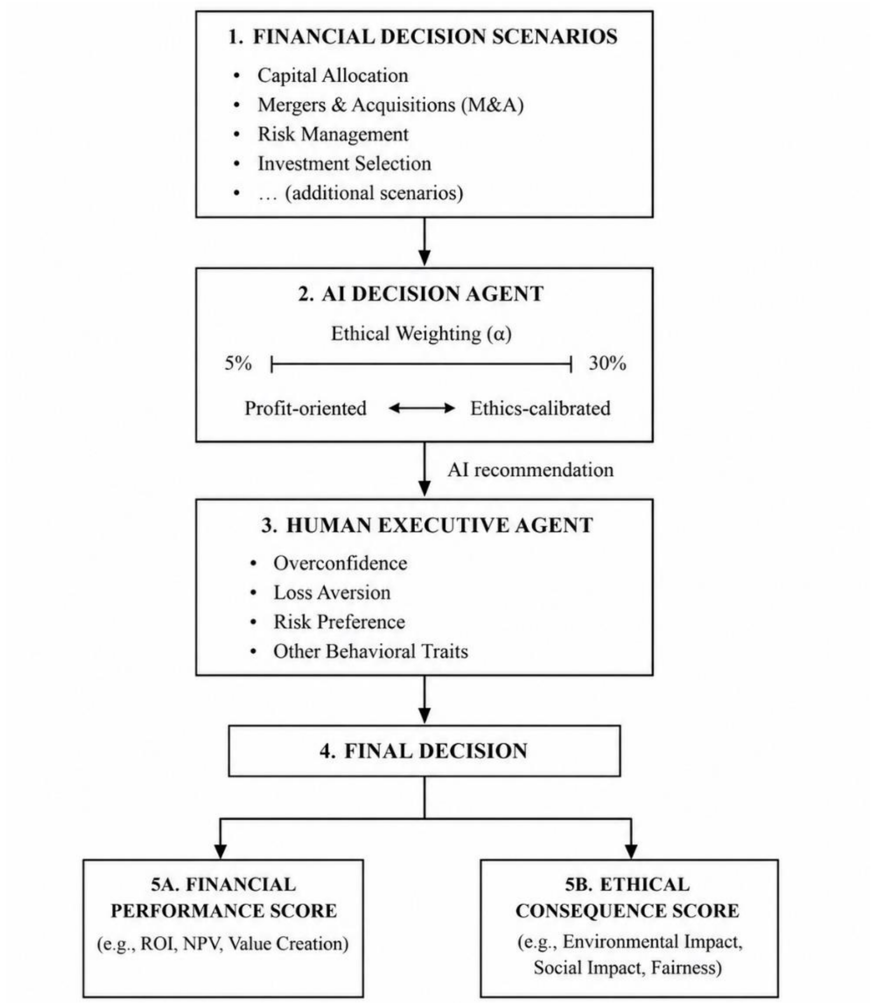

Figure 1. Conceptual Framework of Ethical Trade-offs in AI-Augmented Financial Decision-Making

As shown in Table 1, each theoretical domain provides valuable insights but operates largely in isolation: ethical decision-making offers normative guidance but lacks empirical quantification; behavioral finance identifies biases but does not fully address their interaction with AI systems; AI governance proposes principles but offers limited implementation guidance; and simulation methodologies provide analytical tools but have not been systematically applied to ethical financial contexts. This lack of integration creates a critical gap in both governance design and managerial applicability. Addressing this gap requires frameworks that can simultaneously model ethical trade-offs, behavioral dynamics, and AI system behavior within a unified analytical structure. This study responds to these challenges by developing an integrative framework that embeds ethical analysis, behavioral insights, governance principles, and simulation methodology within executive financial decision-making.

Figure 1 presents the conceptual framework of ethical trade-offs in AI-augmented financial decision-making. The model illustrates a structured decision pathway beginning with financial scenarios that embed ethical considerations, followed by AI systems configured with varying ethical–profit weightings. These AI-generated recommendations are evaluated by executive agents characterized by behavioral biases such as overconfidence, loss aversion, and risk preferences. The resulting decisions are assessed using both financial performance scores and ethical consequence scores. Crucially, this framework operationalizes AI governance principles by translating abstract ethical requirements into measurable decision variables. From a managerial standpoint, it provides a decision-support structure that enables systematic evaluation of trade-offs, thereby supporting more informed and accountable financial strategy development.

III. RESEARCH METHODOLOGY

A. Research Design and Simulation Architecture

The design and approach used in this study are quantitative and based on a bespoke agent-based simulation model. Simulation techniques provide strong advantages for analyzing counterfactual decision systems, as widely demonstrated in management and engineering research (Arora et al., 2021; Tao et al., 2022). In this study, multiple interacting agents specifically AI agents and human executive agents are embedded within predefined decision scenarios to evaluate outcome dynamics. The structure follows a dyadic interaction logic where algorithmic recommendations and human behavioral responses jointly determine final decisions. The methodological contribution of this design lies in its integration of behavioral finance constructs and AI decision logic within a unified simulation architecture, enabling systematic observation of ethical–financial trade-offs under controlled conditions. Implementation is conducted using Python-based simulation libraries and statistical tools to ensure analytical rigor. To enhance reproducibility, the model structure explicitly defines agent roles, decision rules, utility functions, and interaction sequences, allowing independent replication of simulation logic and outputs. Tracing capabilities are fully embedded to capture decision pathways from parameter initialization to final outcome evaluation, supporting transparency in line with AI governance principles (Lu et al., 2024).

B. Scenario Development and Parameterization

The ten strategic financial scenarios were developed through a structured synthesis of prior literature, documented case studies, and expert-informed judgment to ensure both

Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 79-96

theoretical grounding and practical relevance. These scenarios such as "Sustainable Investment in Emerging Markets" and "Merger with Significant Workforce Implications" represent commonly encountered high-stakes financial decisions with embedded ethical dimensions. The selection of scenarios is justified by their frequent appearance in financial decision-making literature and governance discussions, particularly those involving trade-offs between profitability and stakeholder impact.

Table 2. Simulation Scenario Characteristics and Parameters

Scenario ID	Decision Type	Primary Ethical Dimension	Financial Parameters	Ethical Parameters	Conflict Level
SC1	Capital Allocation	Environmental Sustainability	NPV, ROI, Payback Period	Carbon Impact, Community Effect	Low
SC2	Merger Acquisition	Employee Welfare & Fairness	Synergy Value, EPS Impact	Job Losses, Cultural Integration	High
SC3	Risk Management	Transparency & Disclosure	VaR, Expected Loss	Information Quality, Stakeholder Trust	Medium
SC4	Investment Selection	Social Equity Considerations	Expected Return, Risk	Access Equality, Distribution Effects	High
SC5	Cost Optimization	Labor Ethics & Working Conditions	Cost Savings, Efficiency Gains	Wage Impacts, Working Standards	Medium
SC6	Market Expansion	Cultural Sensitivity	Market Share, Growth Rate	Local Impact, Cultural Appropriation	Low
SC7	Product Pricing	Accessibility & Inclusion	Profit Margin, Volume	Affordability, Inclusivity Metrics	High
SC8	Supply Chain	Environmental Ethics	Logistics Cost, Reliability	Sustainability, Ecological Impact	Medium
SC9	Dividend Policy	Stakeholder Equity	Payout Ratio, Yield	Minority Protection, Distribution Fairness	Low
SC10	R&D Investment	Long-term Societal Benefit	Innovation ROI, Time Horizon	Future Generations, Social Value	Medium

Each scenario is parameterized along two primary dimensions: financial utility metrics and ethical consequence indicators. Financial metrics such as Net Present Value (NPV), Internal Rate of Return (IRR), and Earnings Per Share (EPS) are selected due to their widespread use in corporate finance evaluation frameworks. Similarly, ethical indicators including fairness, transparency, social impact, and sustainability are derived from established AI governance principles and responsible innovation literature, ensuring conceptual validity. This dual-parameter structure allows systematic comparison across scenarios while maintaining alignment with both financial theory and AI governance requirements.

Table 2 presents the comprehensive scenario framework used in this study, detailing ten financial decision contexts with varying ethical dimensions and conflict levels. Each scenario reflects a realistic executive decision environment and is parameterized with both financial and ethical indicators. The conflict level classification (low, medium, high) is determined based on the expected degree of divergence between financial and ethical objectives, informed by prior literature and expert calibration. This structured variation enables controlled testing of trade-off intensity across different decision environments. Such design ensures that scenario construction is not arbitrary but grounded in both empirical relevance and theoretical justification**.**

C. Variable Operationalization and Measurement

Independent variables consist of modifiable characteristics of the simulated agents. The AI Decision Agent includes an Ethical Weighting parameter within its utility function, systematically varied between 5% (profit-maximizing) and 30% (ethics-calibrated). These parameter ranges are calibrated based on prior AI governance studies and experimental design logic, where lower bounds represent minimal ethical consideration and upper bounds reflect substantial ethical prioritization without fully overriding financial objectives. The Human Executive Agent is assigned randomized behavioral profiles, including overconfidence, loss aversion, and risk preference, based on validated behavioral finance constructs (Almansour et al., 2023; Risman et al., 2023; Wu et al., 2022). Dependent variables are measured through Financial Performance Scores and Ethical Consequence Scores, both normalized on a 0–100 scale. The use of normalized composite indices ensures comparability across heterogeneous scenarios while preserving sensitivity to scenario-specific dynamics. Parameter calibration is further supported by iterative testing to ensure stability and meaningful variance in output distributions.

D. Simulation Procedure and Data Collection

The simulation follows a structured and repeatable sequence beginning with scenario initialization and parameter configuration. This is followed by randomized assignment of agent profiles to capture behavioral variability. AI agents generate initial recommendations based on configured ethical weightings, which are then evaluated and potentially modified by human agents. Outcome calculation produces paired financial and ethical scores, and all decision data are systematically recorded. Each scenario is executed over 1,000 iterations, a threshold selected to ensure statistical convergence and robustness of results based on standard simulation practices.

Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 79-96

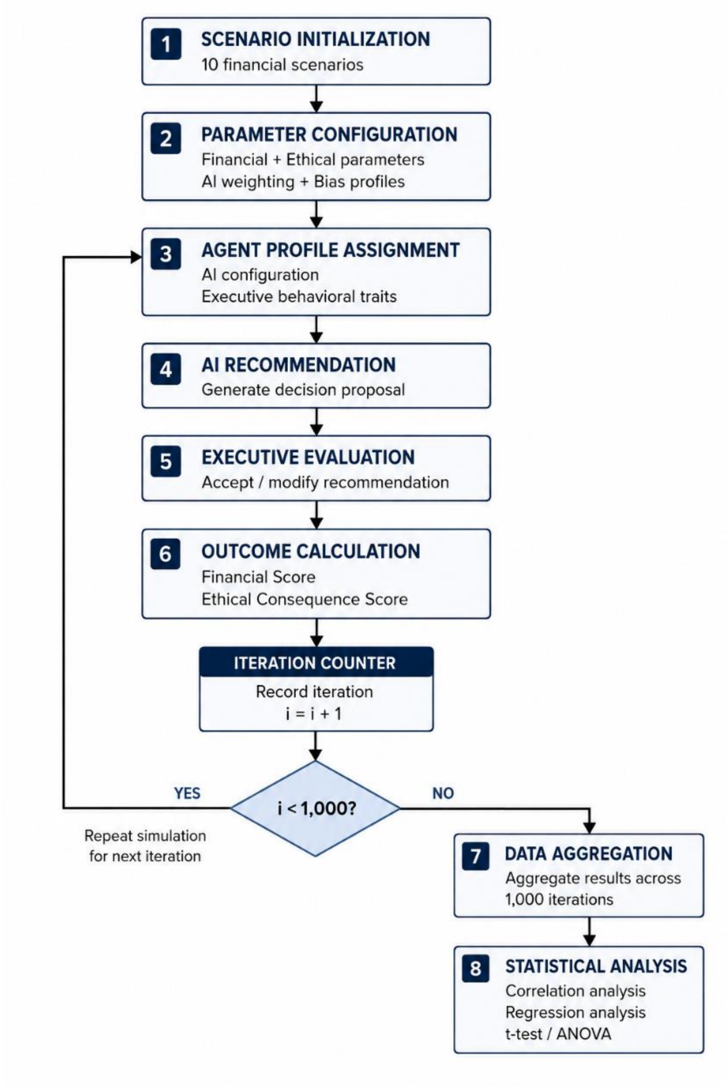

Figure 2. Simulation Procedure Flowchart

The loop control ensures completion of all iterations before aggregation and statistical preparation. The full procedural logic including initialization, agent interaction, decision evaluation, and data recording is explicitly defined to support reproducibility and methodological transparency. Figure 2 illustrates this step-by-step simulation process.

E. Analytical Techniques and Validation

Data analysis employs multivariate statistical techniques to examine relationships among variables and test research propositions. Pearson correlation is used to assess the relationship between financial and ethical outcomes, while multiple regression models evaluate the influence of AI configuration and behavioral traits. Comparative analyses using t-tests and ANOVA examine differences across experimental conditions. Validation procedures are designed to ensure robustness and reliability of findings, including sensitivity analysis, convergence testing, and replication using different random seeds. Sensitivity tests indicate that variations in ethical weighting and behavioral parameters produce consistent directional effects, confirming model stability. These validation methods are sufficient as they address both internal consistency (through convergence and replication) and external plausibility (through sensitivity to parameter changes). All algorithmic processes, decision rules, and bias models are transparently documented. To ensure reproducibility, the simulation code structure, parameter settings, and data processing steps are fully specified, enabling independent verification in line with Open Science principles and avoiding "black-box" limitations in AI systems.

IV. RESULT/FINDINGS AND DISCUSSION

A. *Result*

a) *Descriptive Statistics and Outcome Distributions*

The simulation produced 10,000 complete decision records across ten financial scenarios. Initial analysis reveals substantial variation in outcome distributions, reflecting the experimental design. The average Financial Performance Score is 76.4 (SD 18.2), while Ethical Consequence Scores average 58.7 (SD 23.5), indicating a consistent tension between financial and ethical objectives. Score ranges vary significantly across scenarios, with financial scores between 68.2 and 84.7 and ethical scores between 45.3 and 71.2. These results suggest that, on average, financial optimization tends to dominate ethical considerations, highlighting a structural imbalance in AI-supported decision environments. This imbalance indicates that without deliberate calibration, AI-driven financial strategies may systematically underweight ethical outcomes.

Table 3. Correlation Analysis of Financial-Ethical Trade-offs by Scenario Category

Scenario Category	Number of Scenarios	Average Correlation (r)	Statistical Significance	Interpretation	Representative Scenario
High-Conflict	4	-0.78	$p < 0.001$	Strong negative trade-off	Merger with Layoffs (SC2)
Medium-Conflict	3	-0.31	$p = 0.008$	Moderate trade-off	Supply Chain Ethics (SC8)
Low-Conflict	3	+0.51	$p < 0.001$	Positive alignment	Sustainable Investment (SC1)
Overall Composite	10	-0.19	$p = 0.024$	Net negative relationship	All Scenarios Combined

b) *Trade-off Relationships Across Scenario Types*

Correlation analysis demonstrates strong context dependency in ethical–financial trade-offs. As shown in Table 3, approximately 40% of scenarios exhibit significant negative correlations, while 30% show positive alignment and the remaining 30% indicate weak or neutral relationships. High-conflict scenarios such as workforce reduction cases show strong negative correlations ($r = -0.78$), whereas low-conflict scenarios display positive relationships ($r = +0.51$). This indicates

Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 79-96

that ethical and financial objectives are not inherently conflicting but become so under specific contextual pressures. In high-conflict environments, improving ethical outcomes directly reduces financial performance, whereas in low-conflict scenarios, both objectives can be jointly optimized. Table 3 thus confirms that trade-offs are structurally contingent rather than universal. Table 3 operationalizes the relationship patterns observed in different types of scenarios, thus directly answering the research question on context dependency of ethical trade-offs. Indeed, results reported in Table 3 show that ethical tensions significantly differ depending on scenario characteristics; high-conflict decisions have substantially stronger trade-offs than low-conflict scenarios.

Table 4. Comparative Performance Metrics: AI Configuration Effects

Performance Dimension	Profit-Max AI (5% Ethics)	Ethics-Calibrated AI (30% Ethics)	Absolute Difference	Percentage Change	Statistical Significance
Financial Performance					
Mean Score (All Scenarios)	81.7	71.1	-10.6	-13.0%	$t = 15.34, p < 0.001$
Mean Score (High-Conflict)	86.5	70.9	-15.6	-18.0%	$t = 18.27, p < 0.001$
Standard Deviation	14.2	16.8	+2.6	+18.3%	$F = 1.40, p = 0.012$
Ethical Consequences					
Mean Score (All Scenarios)	49.3	60.8	+11.5	+23.3%	$t = -22.19, p < 0.001$
Mean Score (High-Conflict)	38.9	52.1	+13.2	+33.9%	$t = -25.43, p < 0.001$
Standard Deviation	20.1	17.4	-2.7	-13.4%	$F = 1.33, p = 0.023$
Balance Metrics					
Trade-off Magnitude	32.4	18.3	-14.1	-43.5%	$t = 31.28, p < 0.001$
Optimal Balance Index	0.40	0.58	+0.18	+45.0%	$t = -28.16, p < 0.001$
Ideal Zone Frequency	12.4%	28.7%	+16.3%	+131.5%	$\chi^2 = 412.7, p < 0.001$

c) Effects of AI Configuration on Decision Outcomes

Manipulation of AI ethical weighting produces statistically significant outcome differences. Ethics-calibrated AI increases ethical scores by 33.9% in high-conflict scenarios but reduces financial performance by 18.0%. These results define a measurable trade-off frontier between ethical improvement and financial optimization. This finding indicates that ethical enhancements are achievable but require explicit acceptance of financial opportunity costs. Importantly, the results show that AI configuration acts as a controllable lever, enabling organizations to strategically balance ethical and financial priorities. Table 4 provides quantitative evidence of these trade-offs, representing a core empirical contribution of the study.

Trade-off Magnitude = |Financial Score - Ethical Score| (lower values indicate better balance). Optimal Balance Index = √(Financial Score × Ethical Score)/100 (higher values indicate superior overall performance). Ideal Zone = Both scores ≥ 70 - represents high performance across both dimensions. Detailed evidence for the trade-off frontier between financial and ethical performance has been provided in Table 4, thereby showing that substantial ethical improvements are available at measurable financial costs for ethical AI configurations. As a matter of fact, the estimates in Table 4 are one of the main empirical contributions of this study because these quantify the exact opportunity cost arising from the implementation of ethical AI.

d) Behavioral Factors and Interaction Effects

Regression analysis explains 67% of the variance in ethical outcomes ($R^2 = 0.67$), with all major predictors statistically significant. Executive overconfidence ($\beta = -0.287$) and loss aversion ($\beta = -0.204$) negatively affect ethical outcomes, while AI ethical weighting has a strong positive effect ($\beta = +0.562$). Interaction effects show that overconfidence amplifies the negative impact of profit-oriented AI configurations. This indicates that human behavioral biases can significantly undermine the ethical benefits of AI systems. The findings further suggest that AI governance cannot rely solely on algorithmic design but must also account for human behavioral dynamics. Table 5 confirms that ethical outcomes emerge from the joint interaction of AI and human factors.

Table 5. Multivariate Regression Analysis: Determinants of Ethical Consequence Scores

Predictor Variable	Standardized Beta (β)	t-statistic	p-value	95% Confidence Interval	Variance Inflation Factor
(Constant)	-	45.112	< 0.001	[42.35, 47.89]	-
AI Ethical Weighting	+0.562	18.74	< 0.001	[0.498, 0.626]	1.24
Scenario Conflict Level	-0.691	-25.31	< 0.001	[-0.744, -0.638]	1.18
Executive Overconfidence	-0.287	-10.05	< 0.001	[-0.342, -0.232]	1.32
Executive Loss Aversion	-0.204	-7.88	< 0.001	[-0.256, -0.152]	1.15
Executive Risk Preference	+0.041	1.56	0.119	[-0.011, 0.093]	1.08
AI × Overconfidence Interaction	-0.156	-5.23	< 0.001	[-0.214, -0.098]	1.42
AI × Loss Aversion Interaction	-0.082	-2.89	0.004	[-0.137, -0.027]	1.37
Model R^2	0.67				
Adjusted R^2	0.668				
F-statistic	892.45 ($p < 0.001$)				

Table 5 displays intricate interaction effects between design elements of AI and human behavioral variables. Specifically, it is revealed by the findings that executive bias is a significant moderator of the importance of ethical designs of AI. In total, regression findings of Table 5 indicate support for the relevance of the framework provided by Figure 1.

e) Scenario-Specific Analysis and Contextual Factors

Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 79-96

Scenario-specific analysis highlights the importance of contextual complexity in shaping ethical trade-offs. High-conflict scenarios involving workforce or environmental consequences exhibit stronger trade-offs compared to low-conflict contexts. Decision complexity and uncertainty amplify the influence of both AI configurations and human behavioral traits. This suggests that governance mechanisms must be context-sensitive rather than uniformly applied across decision types. In complex scenarios, both algorithmic settings and executive judgment become critical determinants of ethical outcomes. These findings emphasize the need for adaptive governance strategies in AI-supported financial decision-making.

B. Discussion

The findings of this study provide important conceptual and practical insights into ethical decision-making in AI-augmented financial contexts. Empirical findings show that ethical–financial trade-offs are not fixed but vary systematically across scenarios, supporting contemporary views that ethical decision-making is context-dependent rather than binary (Osasona, Amoo, et al., 2024; Rodgers et al., 2023; Tolmeijer et al., 2022). This extends prior literature by offering quantitative evidence of trade-off structures, which have traditionally been discussed only at a conceptual level. Furthermore, the strong influence of behavioral biases aligns with behavioral finance research (Almansour et al., 2023; Risman et al., 2023; Wu et al., 2022), but this study advances the literature by demonstrating how these biases interact with AI systems to shape ethical outcomes.

From a managerial perspective, the results have direct implications for executives and financial decision-makers. CFOs and senior managers must recognize that AI systems do not inherently produce ethically balanced outcomes and require deliberate calibration of ethical parameters. Additionally, organizations should implement governance mechanisms that mitigate executive biases, such as decision audits, structured override protocols, and bias-awareness training. The findings suggest that effective AI adoption in finance requires not only technical optimization but also behavioral and organizational alignment.

In terms of AI governance and regulatory implications, the study highlights the need for proactive ethical auditing frameworks. Existing governance principles such as transparency, fairness, and accountability (Ayana et al., 2024; Hadfield & Anthropic, 2023; Roberts et al., 2024) are supported, but this study provides operational tools to quantify and monitor these principles in practice. Regulators and policymakers can use such simulation-based approaches to stress-test AI systems before deployment, ensuring compliance with ethical standards while understanding potential trade-offs. This positions simulation as a bridge between abstract governance principles and actionable regulatory practices.

The methodological contribution of this study lies in the development of a replicable simulation framework that integrates ethical, behavioral, and financial dimensions into a unified analytical model. Empirical findings show that both AI configuration and human behavior significantly shape ethical outcomes, with measurable trade-offs across decision contexts. Together, these contributions advance interdisciplinary research at the intersection of AI, finance, and governance.

Despite these contributions, several limitations should be acknowledged. First, the simulation relies on parameterized assumptions that may not fully capture real-world complexity. Second, behavioral profiles are modeled based on generalized constructs rather than real executive data, which may limit external validity. Third, scenario design, while grounded in literature, cannot represent the full diversity of financial decision environments. Future research should incorporate real-world datasets, expand scenario diversity, and explore adaptive AI systems capable of dynamic ethical calibration.

V. CONCLUSION AND RECOMMENDATION

This study provides a robust foundation for using scenario-based simulation to systematically analyze ethical trade-offs in AI-augmented financial decision-making. Methodological contribution of this study lies in the development of a replicable, simulation-based framework that integrates ethical principles, behavioral finance constructs, and AI decision logic into a unified analytical model. The framework enables explicit quantification of tensions between financial performance and ethical consequences across diverse decision contexts. Empirical findings show that ethical–financial trade-offs are both measurable and context-dependent, with high-conflict scenarios exhibiting the strongest negative relationships between the two dimensions. Ethics-calibrated AI improves ethical outcomes by up to 34% but incurs an approximate 18% reduction in financial performance, demonstrating a clear opportunity cost. Additionally, executive behavioral biases particularly overconfidence and loss aversion consistently degrade ethical outcomes, reinforcing the non-neutrality of decision environments involving both human and AI agents.

From a practical perspective, these findings carry significant implications for executives and regulators. For decision-makers such as CFOs and senior managers, the results highlight the need to actively calibrate AI systems, implement bias mitigation mechanisms, and adopt structured ethical evaluation processes in financial strategy. For regulators, the study underscores the importance of developing governance frameworks that incorporate measurable ethical indicators and support proactive auditing of AI-driven decisions. Simulation-based approaches can serve as effective tools for stress-testing AI systems, evaluating policy trade-offs, and ensuring alignment with ethical and regulatory standards. Future research should extend this work by incorporating real-world data, dynamic learning systems, and longitudinal decision processes to enhance external validity and practical applicability.

Statement on AI-Assisted Editorial Enhancement

The authors declare that artificial intelligence tools, including ChatGPT, were utilized exclusively for editorial enhancement to improve grammar, clarity, coherence, and overall readability of the manuscript. All substantive scholarly activities such as research conceptualization, methodological development, data collection, analytical evaluation, interpretation of results, and formulation of conclusions were performed independently by the authors without the involvement of AI systems. The authors accept full responsibility for the originality, accuracy, and academic integrity of the work.

REFERENCES

Almansour, B. Y., Elkrghli, S., & Almansour, A. Y. (2023). Behavioral finance factors and investment decisions: A mediating role of risk perception. In *Cogent Economics and Finance* (Vol. 11, Number 2). Cogent OA. https://doi.org/10.1080/23322039.2023.2239032

Arora, A., Pandey, M., Mishra, V. N., Kumar, R., Rai, P. K., Costache, R., Punia, M., & Di, L. (2021). Comparative evaluation of geospatial scenario-based land change simulation models using landscape metrics. *Ecological Indicators*, *128*. https://doi.org/10.1016/j.ecolind.2021.107810

Ayana, G., Dese, K., Daba Nemomssa, H., Habtamu, B., Mellado, B., Badu, K., Yamba, E., Faye, S. L., Ondua, M., Nsagha, D., Nkweteyim, D., & Kong, J. D. (2024). Decolonizing global AI governance: assessment of the state of decolonized AI governance in Sub-Saharan Africa. *Royal Society Open Science*, *11*(8). https://doi.org/10.1098/rsos.231994

Batool, A., Zowghi, D., & Bano, M. (2025). AI governance: a systematic literature review. *AI and Ethics*, *5*(3), 3265–3279. https://doi.org/10.1007/s43681-024-00653-w

Birkstedt, T., Minkkinen, M., Tandon, A., & Mäntymäki, M. (2023). AI governance: themes, knowledge gaps and future agendas. In *Internet Research* (Vol. 33, Number 7, pp. 133–167). Emerald Publishing. https://doi.org/10.1108/INTR-01-2022-0042

Chai, B. X., Eisenbart, B., Nikzad, M., Fox, B., Wang, Y., Bwar, K. H., & Zhang, K. (2023). Review of Approaches to Minimise the Cost of Simulation-Based Optimisation for Liquid Composite Moulding Processes. In *Materials* (Vol. 16, Number 24). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/ma16247580

Christianah Pelumi Efunniyi, Angela Omozele Abhulimen, Anwuli Nkemchor Obiki-Osafiele, Olajide Soji Osundare, Edith Ebele Agu, & Ibrahim Adedeji Adeniran. (2024). Strengthening corporate governance and financial compliance: Enhancing accountability and transparency. *Finance & Accounting Research Journal*, *6*(8), 1597–1616. https://doi.org/10.51594/farj.v6i8.1509

Dell'Erba, M., & Gomtsyan, S. (2024). Regulatory and investor demands to use ESG performance metrics in executive compensation: right instrument, wrong method. *Journal of Corporate Law Studies*, *24*(1), 1–40. https://doi.org/10.1080/14735970.2024.2350139

Elendu, C., Amaechi, D. C., Okatta, A. U., Amaechi, E. C., Elendu, T. C., Ezeh, C. P., & Elendu, I. D. (2024). The impact of simulation-based training in medical education: A review. In *Medicine (United States)* (Vol. 103, Number 27, p. e38813). Lippincott Williams and Wilkins. https://doi.org/10.1097/MD.0000000000038813

Hadfield, G. K., & Anthropic, J. C. (2023). *Regulatory Markets: The Future of AI Governance*. https://csis-website-prod.s3.amazonaws.com/s3fs-

Jones, K. (2023). *AI governance and human rights Resetting the relationship*.

Lehner, O. M., Ittonen, K., Silvola, H., Ström, E., & Wührleitner, A. (2022). Artificial intelligence based decision-making in accounting and auditing: ethical challenges and normative thinking. *Accounting, Auditing and Accountability Journal*, *35*(9), 109–135. https://doi.org/10.1108/AAAJ-09-2020-4934

Lu, Q., Zhu, L., Xu, X., Whittle, J., Zowghi, D., & Jacquet, A. (2024). Responsible AI Pattern Catalogue: A Collection of Best Practices for AI Governance and Engineering. *ACM Computing Surveys*, *56*(7). https://doi.org/10.1145/3626234

Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Defining organizational AI governance. *AI and Ethics*, *2*(4), 603–609. https://doi.org/10.1007/s43681-022-00143-x

Maulida, A.-Z., & Permata Sari, S. (2023). *Behavioral Finance and Financial Literacy Affecting Investor Millenial Decision Making Process on Sharia Stock*. www.iarjournals.com

Meisa Dai, R., Kostini, N., & Wulan Tresna, P. (2021). *The Influence of Financial Attitude and Financial literacy on Behavioral Finance: A Study on Leading Small and Medium Enterprises in Cimahi City, Indonesia*.

Narne, S., Adedoja, T., Mohan, M., & Ayyalasomayajula, T. (2023). AI-Driven Decision Support Systems in Management: Enhancing Strategic Planning and Execution. In *International Journal on Recent and Innovation Trends in Computing and Communication*. http://www.ijritcc.org

Oktavia, A., & Wibowo, A. (2025). A New Theoretical Framework For Analyzing The Social And Economic Impacts Of Artifical Intelligence Within The Digital Economy. *Journal of Management and Informatics*, *4*(2), 859–871. https://doi.org/10.51903/jmi.v4i2.156

Osasona, F., Amoo, O. O., Atadoga, A., Abrahams, T. O., Farayola, O. A., & Ayinla, B. S. (2024). Reviewing The Ethical Implications Of Ai In Decision Making Processes. *International Journal of Management & Entrepreneurship Research*. https://doi.org/10.51594/ijmer.v6i2.773

Osasona, F., Oladipupo Amoo, O., Atadoga, A., Oluwaseun Abrahams, T., Ajoke Farayola, O., & Samson Ayinla, B. (2024). Reviewing The Ethical Implications Of Ai In Decision Making Processes. *International Journal of Management & Entrepreneurship Research*, (1). https://doi.org/10.51594/ijmer.v6i

Owusu-Mensah, D., Sarfo, P. A., & Kusi, G. A. (2025). Exploring the Impact of Artificial Intelligence on Customer Experience Personalization and Marketing Strategy Optimization in Digital Marketing: An Empirical Analysis. *Journal of Management and Informatics*, *4*(2), 822–843. https://doi.org/10.51903/jmi.v4i2.242

Pembi, S., & Ali, B. K. (2024). Ethical Business Decision-Making in Organizations: A Theoretical Perspectives. *Advanced Qualitative Research*, *2*(1), 19–30. https://doi.org/10.31098/aqr.v2i1.2133

Rachmawati, T. S. N., Park, H. C., & Kim, S. (2023). A Scenario-Based Simulation Model for Earthwork Cost Management Using Unmanned Aerial Vehicle Technology. *Sustainability (Switzerland)*, *15*(1). https://doi.org/10.3390/su15010503

Risman, A., Ali, A. J., Soelton, M., & Siswanti, I. (2023). The behavioral finance of MSMEs in the advancement of financial inclusion and financial technology (Fintech). *The Indonesian Accounting Review*, *13*(1), 91–101. https://doi.org/10.14414/tiar.v13i1.3213

Roberts, H., Hine, E., Taddeo, M., & Floridi, L. (2024). Global AI governance: barriers and pathways forward. *International Affairs*, *100*(3), 1275–1286. https://doi.org/10.1093/ia/iiae073

Rodgers, W., Murray, J. M., Stefanidis, A., Degbey, W. Y., & Tarba, S. Y. (2023). An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes. *Human Resource Management Review*, *33*(1). https://doi.org/10.1016/j.hrmr.2022.100925

Romano Alho, A., Sakai, T., Oh, S., Cheng, C., Seshadri, R., Chong, W. H., Hara, Y., Caravias, J., Cheah, L., & Ben-Akiva, M. (2021). A Simulation-Based Evaluation of a Cargo-Hitching Service for E-Commerce Using Mobility-on-Demand Vehicles. *Future Transportation*, *1*(3), 639–656. https://doi.org/10.3390/futuretransp1030034

Şentürk Erenel, A., Şengül, •, Sözbir, Y., Mehtap, •, Aksoy, U., Esra, •, Gürcüoğlu, A., Sıdıka, •, Aksu, P., Filiz, •, Toprak, Ü., Canan, •, & Asalioğlu, U. (2020). *Effect of Scenario-Based Simulation Training on the Obstetrics and Gynecology Nursing Clinical Practicum*.

Svellingen, A. H., Søvik, M. B., Røykenes, K., & Brattebø, G. (2021). The effect of multiple exposures in scenario-based simulation—A mixed study systematic review. *Nursing Open*, *8*(1), 380–394. https://doi.org/10.1002/nop2.639

Taeihagh, A. (2025). Governance of Generative AI. In *Policy and Society* (Vol. 44, Number 1, pp. 1–22). Oxford University Press. https://doi.org/10.1093/polsoc/puaf001

Tao, F., Kishita, Y., Scheller, C., Blömeke, S., & Umeda, Y. (2022). Designing a Sustainable Circulation System of Second-life Traction Batteries: A Scenario-based Simulation Approach. *Procedia CIRP*, *105*, 733–738. https://doi.org/10.1016/j.procir.2022.02.122

Tolmeijer, S., Christen, M., Kandul, S., Kneer, M., & Bernstein, A. (2022). *Capable but Amoral? Comparing AI and Human Expert Collaboration in Ethical Decision Making*. https://doi.org/10.1145/3491102

Wu, C. C., Yan, Y., Yuan, T., Huang, C. C., & Tsai, Y. J. (2022). A Study of Network Negative News Based on Behavioral Finance Analysis of Abnormal Fluctuation of Stock Price. *Discrete Dynamics in Nature and Society*, *2022*. https://doi.org/10.1155/2022/7952532

Yue, S., Khatib, S. F. A., Bajuri, N. H., Sulimany, H. G. H., & Lee, Y. (2025). Executive Ownership and Minority Shareholder Protection: Drivers of Environmental Innovation in China's A-Share Market. *Corporate Social Responsibility and Environmental Management*, *32*(3), 3854–3873. https://doi.org/10.1002/csr.3158

Zheng, K., Shen, Z., Chen, Z., Che, C., & Zhu, H. (2024). Application of AI-empowered scenario-based simulation teaching mode in cardiovascular disease education. *BMC Medical Education*, *24*(1). https://doi.org/10.1186/s12909-024-05977-z

Zhong, Z., Tang, Y., Zhou, Y., Neves, V. de O., Liu, Y., & Ray, B. (2021). *A Survey on Scenario-Based Testing for Automated Driving Systems in High-Fidelity Simulation*. http://arxiv.org/abs/2112.00964