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Augmented Decision-Making in Financial Markets: A Human–AI Co-Creative Approach

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Abstract: This study examines the role of human judgment and artificial intelligence (AI) in financial decision-making. It proposes a co-creative framework in which the final decision combines AI-generated signals with human input. The relative influence of each component may change with market volatility, task complexity, and trust in the AI system. The framework is explored through a 252-trading-day simulation. Three stylized configurations are compared: an AI-only strategy, a human-only strategy, and a hybrid strategy that combines 60% AI input with 40% human input. The assessment includes cumulative and annualized returns, variance, maximum drawdown, and the Decision Quality Score (DQS). DQS is used as a comparative risk-adjusted indicator based on the mean–variance logic of modern portfolio theory. The simulation is intended as a proof of concept rather than a trading forecast. Under the assumptions used, the AI-only strategy generated the highest return and the highest DQS, although it was also associated with the greatest variance and the deepest drawdown. The human-only strategy produced the most conservative performance profile. The hybrid strategy fell between the two, preserving part of the AI model's responsiveness while reducing some of its volatility. The study does not claim that one configuration is universally preferable. Instead, it shows that the allocation of decision authority between humans and AI can lead to different return–risk outcomes. Its main contribution is a structured framework for examining and comparing human–AI collaboration in financial decision-support settings.

Keywords: human–AI co-creativity, augmented decision-making, financial technology, artificial intelligence in finance, hybrid decision systems

1. Introduction

Artificial intelligence (AI) is increasingly being used in the financial sector, in particular in algorithmic trading, investment portfolio management, risk assessment, fraud detection, and advisory services. Its key advantage is the ability to quickly process large amounts of data and identify patterns that are difficult to identify using traditional analytical methods. At the same time, financial decisions cannot always be made solely on the basis of data. They often require professional experience, an understanding of the current market situation, and consideration of possible consequences for clients, investors, or financial institutions. That is why the emphasis is gradually shifting from full automation to models in which a person and an AI system interact in the decision-making process. Under such conditions, AI can generate analytical signals, rank possible alternatives, or record short-term changes in market indicators. The human expert, in turn, interprets the results obtained, critically evaluates them, and, if necessary, adjusts the final decision, especially when the available data does not reflect the full context of the situation.

In this study, this form of interaction is defined as collaborative decision-making. This term is used to describe the process in which human professional judgment and analytical results generated by AI jointly influence the final decision. For example, an investment advisor may use a recommendation generated by an AI system as an initial basis but modify it to take into account the client's risk appetite, a significant market event, or other information not captured by the algorithmic model.

The aim of the article is to develop a formalized approach to studying such interaction in the financial decision-making process. The proposed model considers the final decision as a weighted combination of AI-generated results and human expert input. Unlike approaches that assume a fixed distribution of roles between a human and a system, the proposed framework

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allows for this ratio to change depending on market volatility, the complexity of a specific task, and the level of trust in the AI system. The study develops and evaluates a simulation model of collaborative decision-making by a human and an AI in a financial environment. The analysis aims to explore the possibilities of combining human judgment and AI-generated signals in financial technology decisions and consulting activities. Particular attention is paid to the division of authority between the expert and the AI system, as well as the risks of excessive automation and insufficient transparency of algorithmic models. The proposed framework is designed to provide a systematic assessment of human–AI interaction in the field of financial decisions. Explainability is especially important in cases where users need to understand the basis of recommendations generated by the AI system and maintain meaningful control over the final choice. Therefore, theoretically grounded and user-centered approaches to explainable AI can contribute to increasing the transparency and accountability of human–AI interactions [1].

The study has three objectives:

1) To define and conceptualize the notion of co-creative human–AI decision-making in the financial context.
2) To develop a formal model that represents the interactive dynamics between human judgment and machine intelligence in decision processes.
3) To evaluate the comparative performance of human-only, AI-only, and hybrid decision strategies using realistic, simulation-based financial data.

The combination of a theoretical approach with simulation modeling allows us to form a basis for understanding how hybrid intelligence can be measured, simulated, and improved in practical financial applications.

To overcome these limitations, a decision quality assessment framework is proposed—Decision Quality Score (DQS)—which allows us to evaluate the joint result of human and AI interaction under conditions of uncertainty. The peculiarity of the proposed approach lies in the combination of theoretical modeling with empirical simulation, as well as in comparing the obtained results with standard baseline decision-making scenarios.

Although previous studies have extensively examined human-in-the-loop systems, hybrid decision support, and regulated autonomy in AI-based environments, the approaches often remain fragmented in their treatment of financial decision-making as a holistic and measurable process. Existing works typically focus on algorithmic efficiency, behavioral aspects of trust, or governance issues separately, without proposing a unified framework that integrates decision architecture, adaptive governance, and performance measurement.

The proposed study fills this gap by developing an operational framework for human–AI collaborative decision-making between humans and AI in financial decision-making under different financial conditions. In particular, the contribution of the article is:

1) Introducing a formal adaptive weighting mechanism that models the interaction between human judgment and AI outputs under varying market conditions;
2) Applying a risk-adjusted evaluation construct (DQS) as a comparative metric across decision configurations;
3) Providing a simulation-based exploratory validation of hybrid, human-only, and AI-only strategies.

The article is exploratory in nature. Its purpose is not to prove the predictive superiority of a particular trading strategy or to accurately reproduce the behavior of the real financial market. Instead, the work offers a transparent analytical framework for comparing alternative models of the distribution of authority in financial systems where decisions are made with the joint participation of humans and AI. Thus, a decision quality indicator is used to assess the relationship between profitability and risk in the three configurations. Accordingly, the novelty of this work lies not in the concept of human–AI collaboration itself but in its operationalization as a structured and evaluable decision-making architecture.

2. Literature Review

AI is no longer a side technology in finance. It is used for fraud detection, portfolio management, credit assessment, trading, advisory services, and other activities requiring fast processing of large volumes of information. Vuković et al. [2] have recently reviewed that AI is expanding in financial services, both in customer-facing and back-office functions. At the same time, the authors note that greater use of AI is accompanied by outstanding issues of regulation, transparency, accountability, and operational risk.

The financial logic behind AI-enabled decisions still has close ties to traditional approaches to return and risk. Investment decisions, even with the help of machine learning tools, require a trade-off between expected return and risk exposure, and Markowitz's portfolio theory [3] is still a useful reference point. AI doesn't replace this logic; it just changes the speed, scope, and type of information that can be incorporated into the decision process.

Fraud detection is one major application area. As explained by Bao et al. [4], AI systems can help detect suspicious financial activity by analyzing transaction data at a scale that is difficult to manage manually. Similarly, Yang et al. [5] demonstrate that AI-based fraud detection has not only become more sophisticated but also highlights several practical limitations, such as poor data quality, changing fraud schemes, and complexity in explaining model outputs. These concerns go beyond fraud detection, highlighting a general problem in financial AI: even a technically sound model can be difficult to trust or use responsibly. The same problem can be found in portfolio management and trading. Kirtac and Germano [6] show that sentiment analysis based on large language models (LLMs) can be integrated into portfolio optimization, using reinforcement learning approaches. Their study demonstrates that financial AI is increasingly built on more than just numerical market indicators: it is also built on textual and sentiment-based information. Such expansion may enhance analytical capacity, but it may also make the underlying decision logic less clear to users. That is one reason explainability has become a prominent topic in the financial AI literature.

Černevičienė and Kabašinskas [7] review the development of explainable AI in finance and argue that explanation is especially important where automated outputs affect material financial outcomes. Yeo et al. [8] enhance the discussion by noting that financial explainability should meet the needs of different groups simultaneously, namely, analysts, customers, regulators, and system developers. Mahmud et al. [9] show that algorithm aversion is shaped by factors such as perceived transparency, task characteristics, user familiarity with algorithms, and the degree of control retained by the decision-maker.

Vaccaro et al. [10] demonstrate that combining human and AI inputs does not automatically improve decision quality. The effect depends on the task, the comparative strengths of human and algorithmic judgment, and the way their contributions are coordinated.

The increasing use of AI is also influencing the role of human decision-makers. Far from rendering human expertise obsolete, it has given rise to new forms of interaction between professionals and algorithmic systems. McAfee and Brynjolfsson [11] contend that the main value of digital technologies is often in complementarity. Machines can analyze data at scale and identify patterns quickly; people bring context, experience, strategic judgment, and an understanding of consequences that may not be reflected in the data. Shneiderman [1] advocates for "human-centered AI," arguing that AI should be designed to amplify rather than replace human cognition [12]. Brynjolfsson and McAfee [11] likewise emphasize that the future of AI lies in complementarity, not substitution—where machine capabilities are best used to enhance human expertise [11]. Nagarakanti (2025) provides a framework for integrating cloud-native AI into financial advisory workflows, demonstrating how co-creative interactions can optimize both analytical power and interpretability [13].

Balasubramanian et al. [14] consider organizational implications of replacing or delegating human decisions to machine learning systems. They argue that automation can affect organizational learning as employees may become less involved in the evaluation of decisions and less able to detect unusual cases. This argument is important for finance, where an over-reliance on algorithmic recommendations may reduce professional vigilance. A system may work well under normal conditions but require human intervention when the markets behave differently from historical data.

There have been several recent works directly addressing the issue of how the input of a human and that of an AI can be effectively integrated. Revilla et al. [15] demonstrate that collaborative effort can enhance prediction results where the input of both a human and an algorithm provides different types of knowledge. The work by Van Rooy [16] makes the same point, namely, that a hybrid decision-making system cannot merely consist of having both a human and an algorithm present. The roles, responsibilities, and modes of interaction between them must be clearly specified. In addition, according to Xu et al. [17], proper dependency is crucial for effective collaboration. It means that the user should not blindly follow the AI's recommendation or refuse to consider it just because of its origin.

Li and Tian [18] look at AI-human collaboration as a decision-making process as opposed to a mere technical issue. Kou et al. [19] make a similar case with regard to hybrid finance. According to them, there has been a change from the use of AI tools as separate technologies to a decision system where delegation, the right to override decisions, trust, and governance are interrelated. This is especially relevant in finance due to the nature of the market. In finance, the issue is not about whether AI should be applied but about the extent of decision-making authority that should be delegated to it.

Financial services data back up this point of view. In particular, Nagarakanti [13] talks about AI-based financial advisory systems and states that the benefit of these systems relies on the possibility for human experts to be able to interpret the results of using AI and take part in making the decision. As an example of the empirical evidence of judgment noise reduction by the use of AI in combination with human judgment, Sachan et al. [20] can be cited.

Gaudeul and Giannetti [21] also discuss another related topic in algorithm design in finance. Their results indicate that the potential of being able to override the algorithm decision is important for the user's willingness to use the AI. Those who had the ability to interfere seemed to be more trusting of the system and engaged in its operations. However, on the other hand, their results also illustrate the fact that the involvement of humans may entail certain disadvantages, one of which is increased variability of performance. However, the issues of autonomy and accountability acquire special significance where AI technologies impact financially relevant decisions. In his survey of the ethics of research on algorithmic decision-making in finance, Bhatti [22] raises questions related to human autonomy, equality, transparency, and accountability. Moreover, all these questions are not purely theoretical since the effect of an AI technology on investment advice, credit ratings, or risk distribution has very real implications for people and organizations.

In this case, the problem of regulation is further aggravated by the significant level of autonomy of the AI systems. Dou et al. [23] investigate AI-based trading and prove that even with no interaction between reinforcement learning agents, there might be the emergence of a coordinated effect in the market. These results pose questions regarding price efficiency and market integrity and require some regulation. The example from practical life is given by Anand [12]. He notes that big financial companies use AI technology to enable their clients' operations and transactions. While it is not scientific enough, this fact proves that the problem of regulation and responsibility exists in practice.

Trust still appears to be among the core conditions that allow for an effective implementation of AI. According to Glikson and Woolley [24], users' trust in AI is not only dependent on the technological aspects of AI but also on such factors as reliability, transparency, predictability, and the extent to which users feel in control. In turn, according to Pasquale [25], algorithms that are hard to understand make it hard to determine responsibility, especially when the decisions lead to economically important outcomes. Such problems also emerge within the framework of issues that involve bias, fairness, explainability, and accountability [9].

When taken all together, it is clear that the use of AI in finance should not be based only on its speed or accuracy in predictions. It is capable of enhancing data processing, finding certain patterns that might not have been noticed before, and ensuring consistency in decision-making. The problem is that these tools should make sense to humans and allow humans to interfere where necessary.

However, existing literature offers a lot of knowledge about fraud detection, portfolio optimization, explainable AI, human in the loop, trust, and governance. However, each of these lines of research operates separately from each other. Studies of financial applications of AI usually deal with particular cases or performance [4–6, 23], whereas studies about human–AI collaboration more frequently explore dependency, coordination, or accountability [15–18, 24]. Very few studies are devoted to exploring these questions using a single unified framework.

In order to fill the gap, the current research attempts to build a co-creation approach for the financial decision-making process. The model assumes that the end decision will be an integration of AI and human contributions with certain weight on each contribution. This does not mean that the weights will remain constant. They will be determined depending on the level of volatility, complexity of the task, and the level of trust in the system. The simulation will consider the three types of configuration, namely, AI only, human only, and the hybrid one under identical conditions.

2.1. Theoretical framework

The theoretical framework forms a systematic approach to understanding how human–AI collaboration can improve decision-making in financial markets. It draws on an interdisciplinary body of research, including in the fields of AI in finance, behavioral finance, human-computer interaction, and management ethics. It is due to the fact that it is the interplay of these dimensions that allows for explaining how, when, and why augmented decision-making contributes to better financial results. In order to analyze the essence of the interaction between human beings and intelligent machines in finance, one needs to move beyond the stereotypical understanding of "trends" in technology and pay attention to real processes of interaction. Co-creation in decision-making is not only related to functional specialization, but it is also the development of a dynamic system where both human beings and machines contribute to the result in a meaningful way. This kind of system develops through evolution in the course of constant communication and adaptation to the environment.

This relationship can take different forms. On the one hand, there are systems in which AI performs most of the analytical work, and humans only monitor or approve the results. On the other hand, there are models where the leading role remains with humans, and AI performs supporting functions. Between these poles lies the most promising form—a mutual feedback loop, in which the results of each party influence the actions of the other, creating conditions for joint learning and adaptation.

Similar techniques have been gaining popularity in domains such as asset portfolio management or high-frequency trading. In the former case, the algorithms process vast amounts of data and give recommendations; financial advisers improve them, considering individual preferences of the client, his/her risk profile, or even events that have not been accounted for in the data yet. In the latter case, the AI-based algorithms can detect weak signals on the market invisible to the human eye; however, it is still humans who make strategy guidelines and decisions in times of market turbulence.

Research proves that there are some common characteristics of efficient collaborative decision-making systems. Main constructs of the proposed co-creative decision-making model and their definitions and functions are presented in Table 1.

Complementarity. Man and AI do not replicate each other; rather, they complement each other: the former has interpretation capacity, ethics, and context, whereas the latter has efficiency and scalability. In the opinion of Li and Tian [18], the interaction between humans and AI must be perceived as a formalized decision process wherein the importance of AI lies in its combination with human expertise, coordination, and accountability.

Iterative interaction. The exchange of information should be mutual: the human changes the model, the model reacts to such changes, and as a consequence, both the participants refine their tactics. Recently, it was proven that the interaction between humans and AI not only relies on the correctness of outputs but also on the ability of users to comprehend, evaluate, and trust the recommendations provided by an AI system [10].

Transparency and trust. According to Bhatti [22], the development of algorithms to make decisions in finance implies some problems associated with transparency, accountability, and keeping the meaning of human supervision in case of making decisions in high-risk situations. To be sustainable, the system requires that the user has at least a little idea about AI functioning. The perception of the system as a "black box" leads to low trust, which, in turn, reduces the efficiency of the process. Explainability is especially crucial for financial applications since, in order to use the recommendations given by AI, users should understand the major factors influencing them [17].

The degree of co-creation in the process of decision-making may vary from auxiliary (when AI gives only information, but a person makes the decision) to delegated (when a person determines the goal, and AI makes the decision autonomously), with the augmented level in between (when the decision is made by the collaboration of a human being and AI, with iterations). In most of the existing financial applications, the balance is between the first two options, depending on the speed of market changes and risk level.

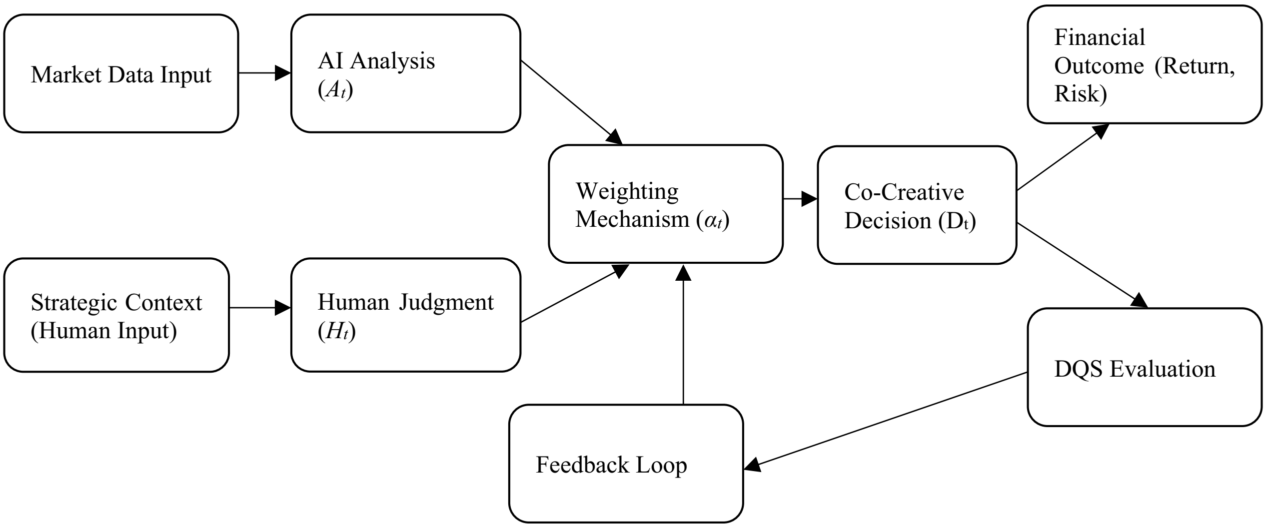
Thus, collaborative decision-making between a human and an AI is not a stable model but a dynamic one, which develops in tandem with the development of technological means, professional practice, and organizational goals. Not only the intellect of AI but also the degree of its adaptation to the actual human process and the level of learning on both sides make such a system effective.

This theoretical framework (Figure 1) is developed on the basis of interdisciplinary knowledge about the definition of a

Table 1
Core constructs and their operational role in the co-creative decision model

Construct	Definition	Operational role in the model	Key references
Artificial Intelligence in Finance (AIF)	Use of algorithmic and machine learning systems in forecasting, trading, and portfolio support	Provides analytical input (A_t)	Balasubramanian and Xu [14]
Human Judgment (HJ)	Contextual, intuitive, and ethically informed financial reasoning	Provides discretionary input (H_t)	Bhatti [22], Kirtac and Germano [6]
Co-Creative Decision-Making (CC)	Joint formation of decisions through complementary human–AI interaction	Captured through weighted combination (D_t)	Revilla et al. [15], van Rooy [16]
Trust Calibration (TC)	Alignment between reliance on AI and its actual reliability	Influences adaptive weighting (α_t)	Dou et al. [23], Nagarakanti [13]
Governance Sensitivity (GS)	Degree to which oversight and accountability are embedded in decision design	Interpreted through dynamic control of (α_t)	Nagarakanti [13]
Decision Quality (DQ)	Risk-adjusted assessment of decision performance	Evaluated through DQS	Kirtac and Germano [6]

Figure 1
Theoretical framework of human–AI co-creative financial decision-making



common financial decision-making framework. It shows how machine intelligence and human experience may be effectively co-optimized under adaptive, transparent, and ethical conditions in order to reach the optimal financial results.

This theoretical framework (Figure 1) illustrates the integration of market data, AI processing, and human experience via the adaptive weighing coefficient (α_t) for reaching the co-creative financial decision. The weighing coefficient is considered not only as a technical parameter but also as a governance-sensitive control variable affected by the issues of trust, volatility, and task complexity.

3. Research Methodology

The current study utilizes an exploratory approach that involves conceptual modeling and simulation-based evaluation of the concept. While the objective of the methodological approach employed is not to prove its predictive superiority compared to other models in the real-life environment, its goal is to put into practice and evaluate, in terms of comparison, how the interaction of human intuition and AI can be achieved within a decision-making framework. Two major deficiencies in the extant literature have prompted the development of the methodological design applied in the study. First, much of the literature discussing human-in-the-loop systems, hybrid decision support, and adjustable autonomy lacks practical focus despite being conceptually well-elaborated. Second, there is insufficient comparative framework for comparing different arrangements of human and AI decision-making. Thus, the methodology consists of two interrelated parts:

1) A formal conceptual model of co-creative decision-making; and
2) A simulation-based proof of concept for comparing AI-only, human-only, and hybrid decision configurations.

The methodological contribution of the study therefore lies in providing a structured and reproducible analytical framework for exploratory comparison, rather than in claiming a finalized empirical model of market behavior.

3.1. Conceptual model of co-creative financial decision-making

To formalize the interaction between human and AI agents in financial decisions, the final decision at time t, denoted as Dt, is modeled as a weighted combination of AI-generated output and human input:

$$Dt = \alpha t At + (1 - \alpha t)\, Ht \tag{1}$$

Where:

Dt = final decision output (e.g., portfolio allocation, trade execution, or investment recommendation);

At = AI-generated analytical output or recommendation;

Ht = human-adjusted or human-generated decision input;

αt = dynamic weighting coefficient representing the relative influence of AI at time t.

This formulation is intended to capture co-creative decision-making as a dynamic process rather than a fixed allocation of authority. In contrast to static automation models, the proposed structure allows the influence of AI and human judgment to vary depending on contextual conditions.

The weighting coefficient αt is conceptualized as a function of three contextual variables:

$$\alpha t = f(Vt, Tt, Ct) \tag{2}$$

Where:

Vt = market volatility or uncertainty;

Tt = calibrated trust in the AI system;

Ct = task complexity or ambiguity.

If the conditions are stable, data-rich, and have low ambiguity, then αt will increase, which means that the operation would be more dependent on signals generated by the machine. Alternatively, if the conditions are volatile, uncertain, or ethically sensitive, then αt will decrease, and human judgment will play a greater part.

Significantly, αt is not considered only from a purely technical perspective. In addition to being a technical parameter, the dynamic weighting parameter (αt) is a governance-sensitive control parameter as well. In essence, αt is a measure of how much decision-making is done by the machine as opposed to the human. High levels of αt imply dependence on algorithm outputs in stable and data-rich environments, while low levels of αt imply dependence on human decision-making in environments that are uncertain, ethically sensitive, or have high levels of systemic risk. This enables the inclusion of governance concerns like accountability, explainability, and controllable autonomy directly in the decision-making process as opposed to being a constraint outside the decision-making process. This simulation is a conceptual exercise and not meant for predictive purposes.

3.2. Operational evaluation using the Decision Quality Score (DQS)

To evaluate the comparative quality of different decision configurations, this study applies the DQS, defined as:

$$DQS = E(R) - \lambda\sigma^2 \tag{3}$$

Where:

$E(R)$ = expected return;
σ^2 = variance of returns;
λ = risk-aversion coefficient.

The DQS is not introduced here as a fundamentally new utility function. Rather, it is used as an applied operational adaptation of classical mean–variance decision utility, consistent with the logic of modern portfolio theory [9]. Its role in this study is comparative and evaluative: to provide a compact index for assessing how alternative decision architectures balance return generation and risk exposure. The DQS was constructed as a risk-adjusted performance measure, drawing on the logic of modern portfolio theory, where expected returns should be assessed together with the variance of returns [9].

This framing is especially relevant in the context of human–AI collaboration, where decision quality should not only be assessed by raw performance outcomes but also by the stability and robustness of those outcomes under uncertainty. Accordingly, DQS is used as one of several complementary indicators rather than as a standalone universal measure of decision optimality.

3.3. Simulation-based experiment

To illustrate the analytical usefulness of the proposed framework, a simulation-based experiment was conducted using synthetic daily return series over 252 trading days, approximating one calendar year of market activity.

This simulation has been constructed as a proof of concept and not a prediction or calibration of the trading model based on market prices. The objective is to conduct a controlled comparison in order to study the implications of varying decision configurations under equal conditions.

Gaussian process was used to generate synthetic market returns:

$$rt \sim N\left(0.0005,\ 0.012^2\right) \tag{4}$$

where the daily mean return (0.0005) and standard deviation (0.012) were selected to approximate stylized return behavior broadly consistent with liquid equity market instruments such as SPY and QQQ.

Three decision configurations were evaluated:

1) AI-only strategy
2) Human-only strategy
3) Hybrid strategy (60% AI / 40% human)

The algorithm-only approach was designed to simulate an approach that is relatively reactive and sensitive to signals, attempting to capture the responsiveness of algorithms to immediate market developments.

The discretionary human approach was designed to reflect a smoother process, trying to simulate the behavior of discretionary decision-making, where corrections are made and context filters information.

The hybrid strategy was constructed as a weighted combination of the two, using the baseline formulation:

$$Dt = 0.60At + 0.40Ht \tag{5}$$

This fixed hybrid weighting was selected for the baseline simulation to maintain internal consistency and interpretive clarity. While the broader theoretical model allows αt to vary dynamically, the simulation uses a constant benchmark weighting to isolate the comparative logic of co-creative decision architecture under stylized conditions.

For each decision configuration, the following performance indicators were calculated:

1) Cumulative return
2) Annualized return
3) Annualized variance
4) Maximum drawdown
5) DQS

The simulation was implemented as a comparative analytical exercise, and the results should therefore be interpreted as illustrative rather than predictive.

Table 2 outlines the three different baseline decision configurations that have been employed in the simulation. The structure of the decision framework has been kept deliberately simple in order to focus on the comparative reasoning about the division

Table 2
Simulation design and decision configurations

Configuration	Mathematical representation	Behavioral logic	Role in comparative evaluation
AI-only	$D_t = A_t$	Reactive, signal-sensitive, algorithmic decision rule	Tests performance under full algorithmic authority
Human-only	$D_t = H_t$	Conservative, heuristic, judgment-based decision rule	Tests performance under full human discretion
Hybrid (60/40)	$D_t = 0.60A_t + 0.40H_t$	Weighted co-creative architecture combining speed and moderation	Tests balance between responsiveness and control

of decision authority among the AI system, the human system, and the hybrid system.

Since this study has involved a simulation-based approach to its empirical component, reproducibility becomes a key issue from a methodology perspective. With this in mind, the simulation framework has been designed in such a way that it involves clearly stated assumptions and parameters and a simple comparative structure which can be reproduced by others. The simulation framework was designed with clearly stated assumptions, decision configurations, weighting logic, and evaluation indicators. The main decision configurations used in the simulation are summarized in Table 2.

There are several limitations to the research methods that need to be mentioned. First, the model utilizes artificial data, not the actual data used in trading. Thus, the results obtained cannot be considered as proof of the empirical value of the model in terms of financial performance. Second, the human and the AI strategies used are abstract representations of such behaviors. Finally, the governance-specific definition of αt is conceptual, not experimental.

Accordingly, the methodological contribution of this paper should be understood as exploratory and structural: it offers a framework for thinking about and evaluating co-creative decision architectures, rather than a finalized predictive model for real-world investment execution.

3.3.1. Results and analysis

Simulation results provide an illustration of the comparison of the behavior of AI-only, human-only, and hybrid decision-making systems in a stylized market environment.

In the 252-day simulation period, the AI-only system demonstrated the highest level of return prospects, attributable to its greater sensitivity to market signals. Nevertheless, the AI-only configuration revealed the greatest level of volatility and instability of performance.

The performance of the three decision-making configurations over the 252-trading-day period is shown in Table 3. The AI-only system has provided the maximum return on average (0.32%) yet also demonstrated a considerable level of volatility. In contrast, the human-only configuration has been rather conservative, showing a lower return (0.22%), yet having the same drawdown. A good compromise has been the hybrid system with the return close to that of the AI system and better stability in terms of drawdown (DQS = 0.303).

These simulated returns follow realistic behavior patterns based on SPY/QQQ-like assets:

1) AI returns: ~12% annualized, with ~20% annualized volatility.
2) Human returns: ~5% annualized, with ~10% volatility.
3) Hybrid: smoother growth curve.

The human-only strategy produced a more conservative trajectory. Although the return generation was smaller, it showed a more even course and lower risk exposure, indicating the effect of heuristics and less reactivity.

The hybrid system held an intermediate place between these two. It had kept a considerable part of the return responsiveness that the AI system had but lowered its volatility at the same time. This made the hybrid system look more balanced between the responsiveness and control aspects.

These findings support the theoretical premise of the study, according to which the co-creative decision architecture might be analytically valuable not due to the fact that it always outperforms single-agent decision-making structures, but due to the ability of such structures to bridge the gap between speed and judgment. The obtained results of the simulation illustrate the behavior of the three decision configurations under identical conditions in a stylized market.

According to the data presented in Table 3, the AI-only strategy resulted in the highest cumulative return (14.18%) and annualized return (17.03%). Nevertheless, the high returns were followed by the highest annualized variance (4.95%) and the greatest maximum drawdown (−19.73%).

The human-only model delivered the most conservative results. Despite having the smallest cumulative return (3.75%) and the smallest annualized return (4.84%), it had the smallest variance (2.09%) and the smallest maximum drawdown (−14.32%). This is consistent with the idea that discretionary, intuitive decision-making processes can be more focused on stability than responsiveness.

The hybrid model was an intermediary one. It earned the cumulative return of 10.03% and the annualized return of 11.99% but still managed to have smaller variance (3.55%) and smaller drawdown (−17.59%) than the AI-based only one. This means that the hybrid approach had quite a bit of responsiveness of algorithmic decisions left.

The DQS provides an additional point of view for interpretation of the comparative trade-offs among the three decision architectures.

The AI-only framework exhibited the greatest DQS measure (0.071), due to better performance in return generation although with higher variance. The hybrid framework exhibited a positive yet lower DQS measure (0.049), which shows some degree of moderation between return and variance. The human-only framework exhibited the lowest DQS measure (0.007), showing that stabilization was not enough to offset its low return generation under the premises of this simulation.

It is important to note that these findings cannot be interpreted as proof of any form of superiority of one type of framework over the other. Instead, they serve as examples of how varying amounts of human and AI powers can result in different

Table 3
Comparative performance of simulated decision configurations

Configuration	Cumulative return (%)	Annualized return (%)	Annualized variance (%)	Maximum drawdown (%)	Decision Quality Score (DQS)
AI-only	14.18	17.03	4.95	–19.73	0.071
Human-only	3.75	4.84	2.09	–14.32	0.007
Hybrid (60/40)	10.03	11.99	3.55	–17.59	0.049

Note: Results are based on a stylized 252-trading-day simulation using synthetic daily return series calibrated to approximate broad-market equity behavior. Values are intended for comparative analytical interpretation rather than predictive inference.

balances of returns and risks based on the performance criterion used.

The findings of this simulation are also important for the governance of human–AI finance frameworks.

Whereas purely AI-based systems are correlated with better responsiveness but increased instability, purely human-based systems have stronger moderation capabilities but reduced adaptability, and a hybrid model would present a more manageable middle path. In such an interpretation, the benefit of co-creative decision-making is not only about balance in terms of performance but also control over resource allocation.

This makes the relevance of the weighting mechanism αt. In real-world financial settings, the ability to calibrate how much authority is delegated to AI under changing market, trust, and complexity conditions may be as important as the predictive accuracy of the AI itself.

3.4. Governance and risk considerations in co-creative financial decision-making

While human–AI co-creative systems offer important analytical and practical advantages in financial decision-making, they also introduce governance-sensitive risks that should be considered alongside performance outcomes.

The key issue is that of the misalignment of decision-making control. Should too much control be assigned to the AI in unstable or uncertain situations, then there is a risk of the AI being too reactive and exaggerating any noise, volatility, or particular weaknesses of its own models. On the other hand, should human supervision still carry excessive weight in very stable settings, then the efficiency benefits of the algorithms could be left unrealized. From this perspective, αt is not only a numerical parameter but also a control one.

A second challenge concerns explainability and accountability. In co-creative systems, decision outcomes are jointly shaped by algorithmic and human inputs, which can make responsibility attribution less straightforward than in purely manual or purely automated settings. This reinforces the importance of interpretable decision support, transparent override structures, and explicit governance protocols regarding when and how AI recommendations may be accepted, adjusted, or rejected.

A third consideration relates to institutional design. However, the practical potential of such co-creative systems is not only linked to their predictive power but also to their incorporation into the organizational decision-making process where this process can be verified and monitored. In this regard, the suggested approach implies that collaboration between humans and machines in finance should be regarded as a design task requiring trust tuning, controlled autonomy, and role assignment.

The above-listed implications are still exploratory in this research. They are not experimentally tested through human or regulatory behavior tests but rather analyzed using the structure of the suggested model. Future research may extend this framework by testing how alternative weighting schemes, trust conditions, or override rights affect both performance and accountability in real or experimental financial environments.

4. Conclusion

This study contributes to the growing literature on augmented intelligence in finance by proposing an operational framework for modeling and evaluating human–AI co-creative decision-making. Rather than presenting human–AI collaboration as a brand-new idea on its own, the paper takes the conversation further through the formalization of ways that human judgment can interact with AI-generated results in a financial decision framework.

The core of the suggested framework will be formed by the concept of a weighted decision model, the weights used within which could be regarded both from the perspective of a purely technical issue and as a governance-oriented device for controlling decision-making authority depending on the evolution of market circumstances.

As the basis for the comparative analysis of various types of decision-making architecture, the framework will employ the DQS, which is considered an operational implementation of the classical risk-adjusted utility approach. In this context, DQS could be seen as a convenient instrument for studying the relationship between gain creation and risk-taking and not as a new theoretical construct.

In terms of the simulation-based results, it is possible to conclude that the AI-only, human-only, and hybrid approaches provide unique performance characteristics within the hypothetical market environment. The AI-only approach demonstrated the best performance characteristics in terms of the return response, yet the largest values of both the volatility and drawdown were achieved. The human-only approach stayed the most conservative and stable; at the same time, the hybrid approach provided a more balanced set of performance characteristics by keeping some analytical capability of AI and avoiding its instability.

The practical significance of the research is based on the idea that human–AI financial systems should be developed taking into account not only the ability to make predictions but also the possibility of adaptability in terms of allocating authority.

A few limitations of the study need to be addressed. It uses simulated data instead of actual transaction or decision-making data. The behavioral logic underlying the strategies used in the simulation is not empirically grounded but merely stylized. Also, the governance implications of the model have only been theoretically analyzed but not actually tested. Therefore, the current study should be considered more as a proof of concept rather than a fully developed deployment model.

Further research could pursue several avenues: empirical verification of the model with real financial decision data, sensitivity analysis with alternative weighting methods, and behavioral experimentation with trust calibration, override rights, and accountability for decision-making in the process of human–AI cooperation. These developments would provide insight into the conditions under which collaborative decision-making architecture is most viable, resilient, and manageable in practice.

In conclusion, the current study demonstrates that the real potential of using AI in finance could be in enhancing the adaptive and accountable modes of cooperation between people and intelligent machines.

5. Practical Recommendations and Future Directions

The results of this study can imply some useful insights for organizations considering co-creative human–AI decision systems in the finance domain.

First, it is important to highlight that financial institutions could find it useful in transcending traditional divisions of "human" versus "machine" decision-making processes in favor of a more fluid architecture that allows combining automatic analysis with human judgment. In this setting, weighting tools offered by this study could be used as an analytical framework for configuring the level of the algorithm's impact depending on the market environment and decision conditions.

Second, trust calibration should be approached as a primary design feature, not a behavioral one. Systems offering clear outputs, interpretability of recommendations, and override opportunities seem to enable more sustainable cooperation between humans and algorithms than fully automated solutions or extensive manual overrides.

Third, organizations reviewing the hybrid financial system can find beneficial the performance assessment methods that take into account not only the profitability but also the volatility and drawdowns, as well as the general stability of decisions made. In this way, the DQS can help as an illustrative benchmarking tool in analyzing various decision structures.

However, one should keep in mind that these recommendations cannot be taken too seriously. The current research uses simulated stylized logic and constructed data.

Further research could enhance the practicality of this framework through the inclusion of real-world financial decision data, expert interviews, behavioral experiments, and system audits. This would contribute to an understanding of how co-creative decision structures could be adopted in a manner that is not only analytical but also transparent and reliable.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Liudmyla Bohrinovtseva: Conceptualization, Validation, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Olha Kliuchka:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Iryna Chunytska:** Investigation, Writing – review & editing, Supervision. **Olha Batrak:** Methodology, Formal analysis, Investigation, Writing – review & editing, Visualization. **Oleh Hustera:** Methodology, Software, Validation, Formal analysis, Data curation.

References

[1] Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human–Computer Interaction*, *36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118

[2] Vuković, D. B., Dekpo-Adza, S., & Matović, S. (2025). AI integration in financial services: A systematic review of trends and regulatory challenges. *Humanities and Social Sciences Communications*, *12*(1), 1–29. https://doi.org/10.1057/s41599-025-04850-8

[3] Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.2307/2975974

[4] Bao, Y., Hilary, G., & Ke, B. (2022). Artificial intelligence and fraud detection. In V. Babich, J. R. Birge, & G. Hilary (Eds.), *Innovative technology at the interface of finance and operations: Volume I* (pp. 223–247). Springer International Publishing. https://doi.org/10.1007/978-3-030-75729-8_8

[5] Yang, H., Shukur, Z., & Sahran, S. (2026). A review of artificial intelligence for financial fraud detection. *Applied Sciences*, *16*(4), 1–32. https://doi.org/10.3390/app16041931

[6] Kirtac, K., & Germano, G. (2025). Leveraging LLM-based sentiment analysis for portfolio optimization with proximal policy optimization. In *Proceedings of the 1st Workshop for Research on Agent Language Models*, 160–169. https://doi.org/10.18653/v1/2025.realm-1.12

[7] Černevičienė, J., & Kabašinskas, A. (2024). Explainable artificial intelligence (XAI) in finance: A systematic literature review. *Artificial Intelligence Review*, *57*(8), 216. https://doi.org/10.1007/s10462-024-10854-8

[8] Yeo, W.J., Van Der Heever, W., Mao, R., Cambria, E., Satapathy, R., & Mengaldo, G. (2025). A comprehensive review on financial explainable AI. *Artificial Intelligence Review*, *58*, 189. https://doi.org/10.1007/s10462-024-11077-7

[9] Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change*, *175*, 121390. https://doi.org/10.1016/j.techfore.2021.121390

[10] Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour*, *8*(12), 2293–2303. https://doi.org/10.1038/s41562-024-02024-1

[11] McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. USA: W. W. Norton & Company.

[12] Anand, N. (2025). *JPMorgan says AI helped boost sales and client activity in market turmoil*. *Reuters*. https://www.reuters.com/business/finance/jpmorgan-says-ai-helped-boost-sales-add-clients-market-turmoil-2025-05-05

[13] Nagarakanti, R. C. (2025). Human–AI collaboration in financial services: Augmenting decision-making with cloud-native intelligence. *European Journal of Computer Science and Information Technology*, *13*(22), 23–41. https://doi.org/10.37745/ejcsit.2013/vol13n222341

[14] Balasubramanian, N., Ye, Y., & Xu, M. (2022). Substituting human decision-making with machine learning: Implications for organizational learning. *Academy of Management Review*, *47*(3), 448–465. https://doi.org/10.5465/amr.2019.0470

[15] Revilla, E., Saenz, M. J., Seifert, M., & Ma, Y. (2023). Human–artificial intelligence collaboration in prediction: A field experiment in the retail industry. *Journal of Management Information Systems*, *40*(4), 1071–1098. https://doi.org/10.1080/07421222.2023.2267317

[16] van Rooy, D. (2024). Human–machine collaboration for enhanced decision-making in governance. *Data & Policy*, *6*, e60. https://doi.org/10.1017/dap.2024.72

[17] Xu, G., Murthy, S. V., & Jia, B. (2025). Enhancing intuitive decision-making and reliance through human–AI collaboration: A review. *Informatics*, *12*(4), 1–36. https://doi.org/10.3390/informatics12040135

[18] Li, H., & Tian, F. (2026). Advancing decision-making through AI-human collaboration: A systematic review and conceptual

framework. *Group Decision and Negotiation*, *35*(2), 1–24. https://doi.org/10.1007/s10726-026-09980-1

[19] Kou, G., Li, Y., Wang, H., & Wang, X. (2026). Human–AI hybrid finance: From AI tools to decision systems. *Financial Innovation*, *12*(1), 1–34. https://doi.org/10.1186/s40854-026-00941-w

[20] Sachan, S., Almaghrabi, F., Yang, J.-B., & Xu, D.-L. (2024). Human-AI collaboration to mitigate decision noise in financial underwriting: A study on FinTech innovation in a lending firm. *International Review of Financial Analysis*, *93*, 103149. https://doi.org/10.1016/j.irfa.2024.103149

[21] Gaudeul, A., & Giannetti, C. (2025). Beyond performance: Exploring trade-offs in the design of financial algorithms. *Journal of Behavioral and Experimental Finance*, *48*(101119). https://doi.org/10.1016/j.jbef.2025.101119

[22] Bhatti, T. (2026). Algorithmic decision-making and human autonomy in finance: A systematic review of AI ethics research. *Journal of Statistical Theory and Applications*, *25*(1), 1–28. https://doi.org/10.1007/s44199-026-00175-w

[23] Dou, W. W., Goldstein, I., & Ji, Y. (2025). AI-powered trading, algorithmic collusion, and price efficiency (No. w34054). *National Bureau of Economic Research*, 1–46. https://doi.org/10.3386/w34054

[24] Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

[25] Pasquale, F. (2015). *The black box society: The secret algorithms that control money and information*. USA: Harvard University Press.

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