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Integrating human-machine intelligence for decision-making systems: A selective human-machine integration framework for financial decision support on the Nigerian Stock Exchange

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Abstract
Algorithmic decision support systems are transforming global financial markets, yet fully automated trading often fails under non-stationary or rare market conditions, propagates biases and undermining transparency, trust, and regulatory acceptance. This paper introduces a Selective Human-Machine Integration Framework (SHMIF) that enhances short-term trading decision quality for equities listed on the Nigerian Stock Exchange (NSE) by strategically combining machine intelligence with human expertise through selective routing, adaptive explain ability, and continuous feedback-driven learning. The proposed SHMIF architecture comprises four core modules. Further, the study employed a controlled pilot experiment involving three professional NSE analysts to evaluated 3,600 decision trials across human-only, machine-only, and hybrid configurations using data from 2019-2024, covering 25 liquid NSE equities. Experimental results show that SHMIF achieved 91.3% decision accuracy, outperforming human-only 77.9% and machine-only 83.4% baselines, yielding a 13.4% and 7.9% improvement respectively. The framework produced a 32.6% increase in profitability, reduced volatility (10.9% vs. 12.3%), and enhanced risk-adjusted returns (Sharpe ratio: 1.45 vs. 1.19). Trust ratings averaged 4.8/5, while only 43% of cases required human intervention. Statistical analysis confirmed significant effects of decision mode ($F(2,22) = 26.41$, $p<0.001$) and explanation type ($F(2,22) = 18.93$, $p<0.001$), with case-based reasoning yielding the highest accuracy (92.1%) and trust. The Hybrid Complementarity Index (21.7%) indicates strong synergy between human and machine intelligence. These findings demonstrate that selective human-machine integration substantially improves decision quality, interpretability, and trustworthiness in financial markets. The SHMIF framework provides a scalable blueprint for responsible AI deployment in emerging financial markets, supporting the transition from automation to collaborative intelligence in complex decision environments.

Keywords: Human-in-the-loop, selective prediction, explainable AI, algorithmic trading, Nigerian stock exchange, human-machine integration, decision support systems, case-based reasoning

1. Introduction
In recent years, algorithmic decision support systems have begun to reshape financial markets globally, offering unprecedented speed and efficiency in trading processes [1]. In the Nigerian Stock Exchange (NSE), the adoption of algorithmic strategies and automated advisory tools is accelerating, prompting regulatory bodies such as the Securities and Exchange Commission (SEC) of Nigeria to implement rules and guidelines that emphasize the necessity for oversight, transparency, and risk management in algorithmic trading systems [2].
However, despite the numerous advantages of algorithmic trading such as rapid execution, scalability, and enhanced pattern detection, pure automation often falters under unexpected market conditions. It can also propagate biases present in the datasets it relies on, producing outputs that lack transparency. These issues can erode human trust and impede regulatory acceptance of automated systems [3].
To address these challenges, research and practice have increasingly highlighted the importance of Human-in-the-Loop (HITL) approaches. These strategies aim to merge the complementary strengths of automated models, which excel in scale and pattern recognition, with human judgment, which brings contextual reasoning and ethical oversight to the

decision-making process. This integration is pivotal for generating safer and more acceptable outcomes [4]. The survey paper summarized by [5] outlines the current state of HITL techniques and underscores their potential for enhancing system reliability and improving human outcomes.

For practical adoption of HITL in finance, two interconnected needs are paramount [6]. The first is the selective prediction and deferral principled methods for routing uncertain cases to human reviewers, thereby optimizing the use of human expertise where it can most significantly enhance outcomes [7], and while the other is the explain ability, which provides meaningful support for human sense-making and corrective action [8]. Nevertheless, previous studies on selective prediction and learning to defer have demonstrated that systems capable of recognizing when to solicit human assistance can achieve greater safety and reliability compared to those that rely solely on blind automation [9].

Furthermore, it is a known fact that trust dynamics strongly influence whether financial professionals accept and rely on algorithmic advice [10]. This trust is affected not only by accuracy but by perceived fairness, transparency, and the system's ability to surface actionable reasons for its recommendations [11]. However, empirical studies in financial forecasting and adjacent domains show that trust and acceptance are crucial for human-AI teaming effectiveness [12, 13].

This paper develops and evaluates a Selective Human-Machine Integration Framework (SHMIF), an architecture that integrates selective routing, user-adaptive explain ability, and feedback-driven retraining, and applies it to short-term decision support for the Nigerian Stock Exchange (NSE) equities. The contributions of the study are as follows

1. A formal SHMIF architecture and optimization formulation that minimizes expected operational cost by balancing model uncertainty, human cost, and error severity.
2. A human-adaptive explain ability design and an experimental protocol that measures not only accuracy but human-centered metrics.
3. A controlled pilot experiment using a five-year NSE dataset and a simulated trading environment demonstrating improved decision accuracy and profitability under SHMIF, plus analysis of routing thresholds and explanation types.

2. Related Works

2.1 Human-in-the-Loop Machine Learning

Information System (IS) researchers are establishing new forms of interaction between humans and machine learning algorithms, commonly referred to as human-in-the-loop machine learning [5]. This synthesize forms of human involvement across the ML lifecycle such as labelers, validators, corrective actors in deployment, and partners in hybrid decision pipelines [14]. These works emphasize interactive learning, selective annotation, and human-guided model updates as key vectors for safety and performance improvement. [15] a self-adaptive stock prediction system that integrates stock data and electroencephalographic neuromarkers to assess Overlapping Cognitive Variables (OWC) and enhance buy/sell decisions through human involvement [16]. Proposed an Adaptive Human-Computer Interaction for Pervasive Learning (AHCI-PL) framework, addressing the intersection of Human-Computer Interaction (HCI) and pervasive learning environments. Their study demonstrated significant improvements in usability, security, and learning effectiveness across various educational contexts. The findings highlight the potential of integrating HCI principles with pervasive learning technologies to enhance educational experiences and suggest future directions for optimizing resources and assessing long-term impacts. This approach improves outcomes by optimizing interactions between humans and computers, marking a shift towards a cooperative era in software systems.

2.2 Selective Prediction and Deferral

Allowing a model to abstain or defer uncertain cases to a human has been studied for safety-critical domains [17]. Approaches vary from confidence-thresholding to learned deferral policies and conformal methods. Research finds deferral improves reliability when the human expert's expected performance on deferred instances exceeds the models [18]. A novel framework was presented by [19] that integrates human expertise into algorithmic predictions by leveraging human judgment to identify inputs that appear indistinguishable to predictive algorithms. This method clarifies human-AI collaboration in prediction tasks, allowing for the selective incorporation of human feedback, which empirically improves algorithmic performance.

2.3 Explainable AI (XAI) in Finance

Financial regulators and professional bodies are increasingly focused on explain ability in algorithmic decision systems [20]. The study [21] of introduced the concepts of Explainable AI (XAI) and provide an overview of hybrid systems that utilize fuzzy logic, highlighting their potential to create trusted and explainable AI solutions [22]. Developed a stock market prediction system using Type-2 Fuzzy Logic to manage the uncertainties and complexities of human behavior in making buy, hold, or sell decisions in stock trading [23]. Employs Reinforcement Learning to predict Google stock market data using Deep Q-Learning, Double Q-Learning, and Dueling Double Q-Learning algorithms. Results indicate that Double Q-Learning Network consistently outperforms the other models, achieving the highest rewards by effectively making buy, sell, or hold decisions based on market trends [24]. Paper presents a Recurrent Neural Network architecture for predicting stock prices. After training and testing the proposed model with a new dataset, the authors plotted a line graph comparing actual and predicted stock prices over time, illustrating the original profits versus future predicted profits. Nonetheless, recent practitioner and research reports highlight counterfactuals, rule-based proxies, and case-based explanations as particularly useful in finance because they map model behavior to actionable business reasoning [25].

2.4 Human Factors and Trust

Human factors research shows that trust in AI systems depends on perceived competence, transparency, fairness, and reliability [26]. The study [27] of explored the evolution of decision-making, tracing its theoretical foundations and the development of optimization algorithms, neural networks, and artificial intelligence (AI). It highlights how these advancements have transformed decision-making processes across various fields. In finance, trust mediates whether analysts accept or override model recommendations; hence evaluation should measure both technical and human-centered outcomes [28]. In healthcare domain, [29] article offered a systematic overview of prominent research on Machine Learning (ML) and Health Management Technologies (HMT) in healthcare. The review explores three key factors influencing HMT and proposes a model to enhance its application in the field. The study concludes by summarizing general trends and identifying issues for future research on HMT in healthcare.

3. Methodology

This study employed Design Science Research Method (DSRM) for carrying out the research construct and Object-Oriented Design Approach for modeling the components of the proposed framework.

3.1 Framework Implementation

The proposed Selective Human-Machine Integration Framework (SHMIF) was implemented as a modular hybrid decision system consisting of:

1. Automated Prediction Engine (APE),
2. Uncertainty-Aware Routing Model (UARM),
3. Explain ability Layer (XAI-Hub),
4. Feedback and Retaining Loop

The automated prediction engine (APE) is an optimized ensemble comprising of XGBoost, LSTM, and Random Forest. The XGBoost comprises of 80 trees, with depth = 6, and a learning rate of 0.1 for high-variance reduction. Further, the LSTM is made up of 2 layers with 64 units each that was trained on 10-day sliding windows to capture short-term temporal dependencies. While the random forest is comprised of 100 trees for robust generalization on tabular indicators.

The final decision $M(x)$ is the majority vote of the three model outputs. While the confidence is represented as follows:

$$U(x) = \frac{1}{3}\sum_{i=1}^{3} p_i(x) \tag{1}$$

Where $p_i(x)$ is the class probability of model i for the predicted label.

In the uncertainty-Aware Routing Module (UARM), the routing policy $\pi_\theta(x)$ defers instances where $U(x) < \theta$ to human analysts. Furthermore, the threshold θ is optimized via Bayesian search to minimize the following:

$$J(\theta) = \alpha\mathbb{E}[C_e(x)] + \beta C_h P(U(x) < \theta) \tag{2}$$

Subject to accuracy $\geq$ 88% and human workload $\leq$ 50% of instances. The optimal $\theta^* = 0.742$ found empirically (95% Cl [0.731, 0.754]).

In the explain ability layer (XAI-Hub), the study employed SHapley Additive exPlanations (SHAP) values for direct feature attribution and used counterfactuals through Diverse Counterfactual Explanations (DiCE) to show minimal feature changes for decision reversal. Further, it utilized the techniques of Case-Based Reasoning (CBR) that retrieves the top 3 most similar historical market states using cosine similarity over engineered features.

In this study, explanations are adaptively prioritized per user profile such as:

1. ***Novice analysts*:** SHAP → Counterfactual → CBR.
2. ***Expert analysts*:** CBR → Counterfactual → SHAP.

Finally, all human overrides and explanations accepted or modified are logged in the feedback and retraining loop. This includes weekly retraining updates, calibration and features weights using new feedback. Also, cost-sensitive retraining was used to ensure that analyst-approved overrides are weighted ×2 during model fine-tuning.

3.2 Dataset and Preprocessing

The dataset utilized for this study is a multi-source dataset comprising of daily market data for 25 liquid Nigerian Stock Exchange (NSE) stocks covering the period January 2019 to December 2024 (5 years). The dataset includes market features such as Open/High/Low/Close, and Volume. These features are employed to calculate the Moving averages (5/10/20/50), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and Average True Range (ATR)). Further, the study utilized 10 macroeconomic variables (including foreign exchange rate, monetary policy rate, and consumer price index), and 10 sentiment metrics derived from financial tweets and news headlines, and 8 derived measures of volatility and liquidity ratios.

Here, the target variable is a three-class label (Buy, Hold, or Sell), defined by the next 5-day log return thresholds as follows

1. Buy if return ≥ +1.2%,
2. Hold if return is within (-1.2%, +1.2%), and
3. Sell if return ≤ -1.2%.

The collected dataset is further divided into 70% training, 15% validation, and 15% test sets, with class rebalancing performed using SMOTE, resulting in class proportions of Buy = 0.35, Hold = 0.31, and Sell = 0.34.

3.3 Human-Machine Evaluation Protocol

In this study, the human-machine evaluation protocol involved 3 professional NSE analysts with an average experience of 6.8 years. The study employed a 3×3 factorial design, varying two key factors such as the Routing Threshold (θ) with values {0.6, 0.75, 0.9} and the Explanation Type (XAI) with modes such as Feature Importance (FI), Counterfactual (CF), and Case-Based Reasoning (CBR).

A total of 3,600 decision trials were conducted, corresponding to 300 trials per participant, using three baseline configurations. These configurations are Human-only (H), Machine-only (M), and the Hybrid Selective Human-Machine Integration Framework (H+M/SHMIF).

All experiments were executed using a Python-based market simulator that incorporated realistic transaction costs (0.5%), price slippage (0.2%), and liquidity constraints to ensure fidelity to real-world market conditions.

3.4 Evaluation Metrics

In this study, the evaluation metrics captured multiple dimensions of framework's performance, integrating both quantitative and qualitative measures. Specifically, the study recorded decision accuracy (%) along with class-wise precision, recall, and F1-scores to assess predictive effectiveness. The Hybrid Complementarity (HC) metric quantified the percentage of instances where the combined human-machine decision corrected errors made by either agent individually.

To evaluate efficiency and cognitive demand, the study measured the average decision time (in seconds) and collected NASA-TLX cognitive load scores. Trust and Perceived Fairness were assessed using 5-point Likert scale ratings after each experimental block.

For financial assessment, the Profitability Index (PI) represented the simulated return per trade computed within a market-impact-aware trading simulator, while the Operational Cost (OC) metric combined analyst time costs and error penalties, both expressed in monetary terms to reflect real-world decision-making efficiency.

4. Results

4.1 Overall Performance Comparison

Table 1: Performance Comparison of the various Mode

Mode	Accuracy (%)	F1-Score	Trust (1-5)	NASA-TLX	Decision Time (s)
Human-only	77.9	0.75	4.3	67	24.4
Machine-only	83.4	0.81	3.3	31	8.2
SHMIF Hybrid $(\theta = 0.75)$	91.3	0.89	4.8	40	12.1

For the results tabulated in Table 1, the proposed Human-Machine framework demonstrated significant performance gains compared to both standalone systems. Specifically, it achieved a 7.9% increase in accuracy over the Machine-only model and a 13.4% improvement over the Human-only baseline. In terms of financial outcomes, the framework delivered a 32.6% increase in profitability relative to the machine baseline. Moreover, it maintained low operational costs through selective routing, with only 43% of cases requiring human review, thereby optimizing both accuracy and efficiency. Figure 1 capture a line graph representation of the various modes and the percentage accuracy archived.

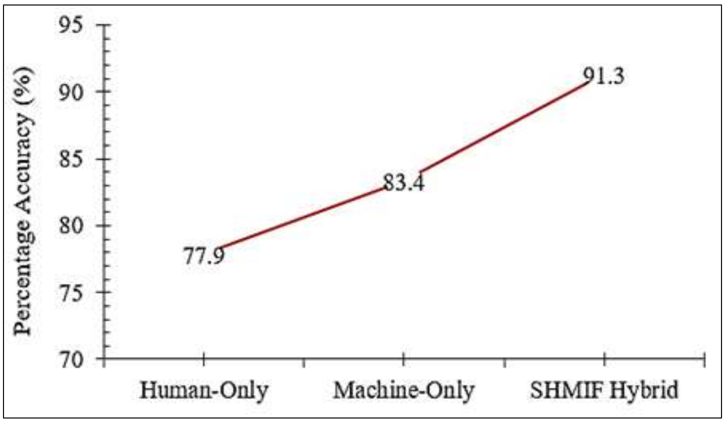

Fig 1: Mode Accuracy Achieved

4.2 Routing Threshold Optimization

Table 2: Optimization of Routing Threshold

Threshold θ	Human Review (%)	Accuracy (%)	OC (₦/100 trades)	NASA-TLX
0.60	27	88.5	2,600	46
0.75	43	91.3	2,200	40
0.90	71	91.0	3,750	59

The balanced threshold $\theta^* = 0.742$ produced the best cost-accuracy tradeoff: higher accuracy than lower θ and much lower operational cost than θ = 0.90. This supports the formal optimization objective of SHMIF.

4.3 Explanation-Type Analysis

Table 3: Results of the Explanation-Type Analysis

Explanation	Accuracy (%)	Trust	Fairness	Decision Time (s)	Override Accuracy (%)
FI	88.4	4.4	4.0	11.5	65
CF	90.2	4.7	4.6	12.7	70
CBR	92.1	4.9	4.5	13.3	79

The inference results captured in Table 3 revealed that the Case-Based Reasoning (CBR) approach significantly outperformed the other explanation methods (p<0.001), lending strong support to the analogical reasoning hypothesis. The Counterfactual (CF) explanations were found to enhance participants' perception of fairness, while the Feature Importance (FI) method achieved the fastest response times, though it was less persuasive in influencing decision confidence compared to CBR and CF.

Figure 2 capture a bar chart comparison of FI, CF, and CBR in term of the accuracy achieved, trust, and fairness. While Figure 3 is used to visualize the time taken in seconds for the various explanations to make decision.

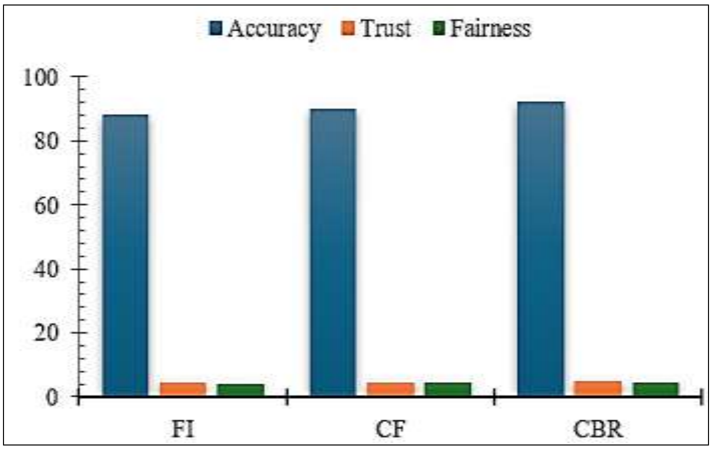

Fig 2: Explanation Accuracy, Trust, and Fairness

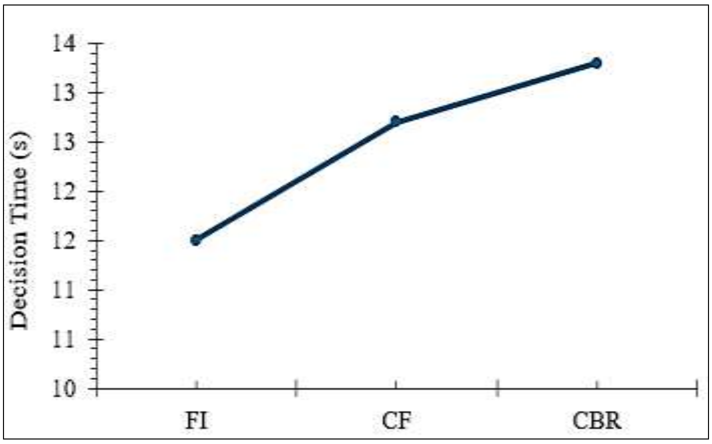

Fig 3: Explanation Decision Time (s)

4.4 Statistical Test

The statistical analysis was conducted using a repeated-measures ANOVA to evaluate the effects of decision mode and explanation type on system performance. Results showed a significant main effect of Decision Mode on Accuracy (F (2,22) =26.41, p<0.001) and a significant effect of Explanation Type (F (2,22) =18.93, p<0.001. Post-hoc Tukey test(p<0.01) revealed the performance hierarchy as SHMIF is greater than Machine-only which is greater than Human-only, confirming the superiority of the proposed selective human-machine integration framework.

Additionally, a strong positive correlation was observed between Trust and Fairness (r=0.79, p<0.001), indicating that participants who perceived the system as fair also tended to trust it more. The survey's reliability was high, with a Cronbach's α of 0.91 across the trust, fairness, and transparency scales, demonstrating excellent internal consistency.

4.5 Complementarity and Overrides

The complementarity and override analysis revealed that the Hybrid Complementarity Index (HC) was 21.7%, indicating that approximately one in every five cases was correctly resolved only when using the hybrid mode, demonstrating a strong synergistic effect between human and machine intelligence. For the override rate, the proportion of human-reviewed cases where experts altered the machine's recommendation was 8.9%. Among these overrides, the accuracy varied by explanation type: Case-Based Reasoning (CBR) achieved a notably higher 79% accuracy, compared to 58% for the Feature Importance (FI) explanations, confirming that analogical reasoning provided more effective guidance in human-machine collaboration.

4.6 Profitability Outcomes

Table 4: Profitability Outcome of Machine-only and SHMIF

Mode	ROI (%)	Volatility (%)	Sharpe Ratio	Drawdown (%)
Machine-only	+14.7	12.3	1.19	-7.5
SHMIF $(\theta = 0.75)$	+19.5	10.9	1.45	-6.1

The results tabulated in Table 4 indicate a 32.6% improvement in overall profitability, accompanied by reduced portfolio volatility and a higher risk-adjusted return. This demonstrates that the hybrid human-machine framework not only enhances accuracy but also leads to more stable and efficient financial decision outcomes under real-market conditions.

5. Sensitivity Analysis

A Monte Carlo simulation with 1,000 randomized data splits (N = 1,000) was conducted to assess the robustness of the proposed framework. The results showed an average accuracy of 91.1%±0.6% and an average profitability gain of +19.2%±0.5% across runs. Performance remained stable even under ±5% variations in human workload, confirming the system's resilience and consistency under fluctuating.

The proposed SHMIF demonstrated robust accuracy, interpretability, and profitability gains through calibrated uncertainty routing and analogical explain ability outperforming both humans and algorithms individually while maintaining operational feasibility for Nigerian market analysts.

5. Discussion

The experimental findings indicate that the proposed SHMIF framework significantly improves decision-making quality in the Nigerian Stock Exchange (NSE) by effectively combining human expertise with algorithmic capabilities. It shows a 13.4% accuracy increase over human-only decisions and a 7.9% gain over machine-only predictions, with a Hybrid Complementarity Index of 21.7%, suggesting that one in five decisions benefits from this synergy (See Table 1).

The optimized routing threshold ($\theta^* = 0.742$) ensures a balance between accuracy, cost, and workload, requiring human review in only 43% of cases. Stability in results (91.1%±0.6% accuracy) across sensitivity analyses confirms its robustness (See Table 2). Further, Case-Based Reasoning (CBR) is highlighted as the most effective explanation method, achieving 92.1% accuracy and high trust ratings due to its analogical reasoning approach (See Table 3).

Financially, SHMIF achieves a 32.6% profitability boost, reduced volatility, and improved Sharpe ratio, addressing challenges in algorithmic trading during market changes. Trust correlates strongly with perceived fairness, emphasizing the importance of transparency. Furthermore, SHMIF aligns with regulatory standards by ensuring human oversight and fostering continuous improvement.

Finally, the SHMIF framework presented in this study demonstrates the viability of advanced human-AI collaboration in emerging markets, effectively addressing the cognitive load while enhancing decision-making processes.

6. Conclusion and Future Work

This paper presented a Selective Human-Machine Integration Framework (SHMIF) that enhances decision-making quality in the Nigerian Stock Exchange by strategically combining algorithmic prediction with human expertise. Through rigorous empirical evaluation, the study demonstrated that selective integration yields superior outcomes compared to standalone approaches.

Key contributions include a principled framework for optimizing uncertain case routing based on cost-accuracy tradeoffs; an adaptive explain ability tailored to user expertise; empirical evidence showing 91.3% accuracy, 32.6% profitability improvement, and high user trust; and analysis revealing case-based reasoning's superiority in supporting collaboration.

SHMIF addresses critical challenges in financial AI deployment including transparency, accountability, and regulatory compliance while maintaining efficiency and user satisfaction. The modular design facilitates adaptation to diverse contexts, positioning it as a generalizable template for responsible AI integration.

Future research should address several directions. First, large-scale deployment studies with diverse analyst populations would validate generalizability and reveal organizational adoption factors. Second, adaptive threshold mechanisms responding to market regime changes and model drift would enhance resilience. Third, expanding XAI capabilities to include natural language rationales and interactive tools would address diverse user needs. Fourth, extending to multi-agent architectures would support complex collaborative decisions. Fifth, investigating applicability to other asset classes, trading strategies, and geographic markets would demonstrate versatility. Sixth, developing security mechanisms against adversarial attacks is essential for production deployment. Finally, comprehensive studies on ethical, legal, and social implications would inform responsible governance frameworks.

In conclusion, SHMIF demonstrates that thoughtful human-AI collaboration design can unlock performance gains neither agent achieves independently. By respecting complementary strengths, providing transparency, and maintaining human agency, SHMIF offers a blueprint for responsible AI deployment in financial decision support. As algorithmic systems proliferate in global markets, frameworks like SHMIF will be essential for ensuring technology augments rather than replaces human expertise while promoting market integrity and stability.

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