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AI AGENTS IN PORTFOLIO REBALANCING: SOLUTION FOR REGRET AVERSION?

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Abstract : This study investigates the intersection of behavioral finance and artificial intelligence (AI) in portfolio management, with a particular focus on how AI-assisted rebalancing can mitigate regret aversion among urban middle-class investors. Drawing on a mixed-methods approach that includes survey data, experimental simulations, regression models, and case studies, the research explores how emotional biases—especially regret aversion—adversely affect rebalancing behavior and portfolio performance. The results reveal that investors with higher levels of regret aversion engage in emotionally driven behaviors such as holding losing assets, delaying reentry after downturns, and hesitating to rebalance, leading to measurable reductions in annualized returns. However, AI-based portfolio management, particularly hybrid systems combining human and machine intelligence, significantly improves rebalancing efficiency, risk-adjusted returns, and behavioral stability. Investors using AI tools displayed lower anxiety, faster decision-making, and fewer emotional trading errors. Moreover, trust in AI—shaped by algorithm transparency, human oversight, and error correction—emerged as a critical factor influencing adoption and satisfaction. The study concludes that AI can serve as both a performance enhancer and a psychological stabilizer in investment decision-making, offering a robust solution for mitigating emotional bias and promoting long-term financial health.

***IndexTerms* – Behavioral Finance, Regret Aversion, Portfolio Reblancing, Artifical Intelligence, Investor Bias, Trust in AI, Emotional Trading, Risk-Adjusted Returns, Hybrid Investment Models, AI Adoption, Middle-Class Investors**

I. INTRODUCTION

Portfolio rebalancing is a cornerstone of strategic investment management, essential for maintaining an optimal risk-return profile in dynamic market conditions. Yet, despite its importance, many individual investors fail to rebalance their portfolios systematically, often due to the influence of behavioral biases. Among these, regret aversion stands out as a particularly detrimental force—driving investors to avoid making necessary changes out of fear of realizing losses or making future-regrettable decisions. This emotional inertia leads to poorly timed decisions, missed opportunities, and long-term underperformance.

Within the broader discourse of behavioral finance, regret aversion has been consistently linked to lower trading frequency, inefficient asset allocation, and excessive loss avoidance. The psychological discomfort associated with potential regret results in investors holding on to losing investments for too long or hesitating to re-enter the market after downturns. These behaviors, while emotionally rationalized, conflict with the principles of effective portfolio management.

In response to these challenges, the integration of Artificial Intelligence (AI) into financial services—particularly in portfolio rebalancing—has gained significant momentum. AI systems offer the potential to mitigate emotional biases by automating decision-making, providing consistent logic, and reacting in real-time to changing market conditions. Advanced models, including reinforcement learning and hybrid AI-human frameworks, are now capable of making tactical allocation adjustments with minimal psychological distortion. These systems not only outperform traditional approaches in terms of risk-adjusted returns but also appear to reduce stress, delay, and irrationality in investment behavior.

However, the successful adoption of AI in portfolio management depends on more than technical performance. Investor trust, perceptions of transparency, and the desire for human oversight continue to shape how individuals interact with AI-based systems. Understanding these psychological and behavioral dimensions is crucial for designing AI tools that are not only effective but also acceptable to the people they are meant to assist.

This research investigates how AI-assisted portfolio rebalancing can mitigate regret aversion and other behavioral biases among urban middle-class investors. It evaluates the effectiveness of AI across key investment performance metrics while also examining trust, adoption barriers, and user satisfaction. The study uses a robust mixed-methods design, integrating empirical analysis with psychological insights, to contribute both to the field of behavioral finance and the practical implementation of AI in wealth management.

II. LITERATURE REVIEW

2.1 Impact of Regret Aversion on Portfolio Rebalancing Decisions

Regret aversion is a well-documented behavioral bias where investors avoid making decisions that might later cause psychological regret. This reluctance results in delayed portfolio rebalancing, **inefficient asset allocation**, and **missed opportunities for optimal investment outcomes**.

A study (Shafqat & Malik, 2021) conducted on **384 investors on the Pakistan Stock Exchange (PSX)** found a significant **negative correlation (r = -0.401, p = 0.003) between regret aversion and trading frequency**, suggesting that regret-averse investors trade less frequently due to fear of potential losses. Moreover, **45% of investors exhibit regret aversion tendencies**, leading to defensive investment behavior and reduced trading frequency (**Shafqat & Malik, 2021**).

Further research highlights that investors who delay rebalancing due to regret aversion experience an **average portfolio underperformance of 7% annually** compared to those who follow systematic rebalancing strategies ***(Meta-Analytical Study on Emotional Biases & Investment Decisions, 2024).***

Herd behavior, a consequence of regret aversion, influences **60% of investors**, prompting them to follow peer investment trends rather than making rational, independent decisions (**Adedoyin, 2024**). This behavior often results in misaligned portfolios and increased market volatility. Additionally, **38% of regret-averse investors delay selling underperforming assets**, further exposing themselves to higher portfolio volatility and potential losses (**Yusuff, 2022**). Missed rebalancing opportunities caused by hesitation and emotional inertia lead to a **7-12% lower annualized return** for regret-averse investors compared to their more active counterparts (**Jiang et al., 2020**).

Studies also reveal that investors with high regret sensitivity are **35% less likely to rebalance their portfolios**, even when optimal conditions arise, leading to overconcentration in certain asset classes and exposing portfolios to increased risk and volatility ***(AI-Driven Portfolio Optimization: Enhancing Investment Strategies Using Machine Learning, 2024)***.

AI-driven portfolio management provides an effective solution to mitigate the effects of regret aversion by employing algorithmic decision-making that ensures consistent and bias-free asset reallocation. **Reinforcement Learning (RL)-based AI models** have shown the capability to improve rebalancing adherence by **22% among regret-averse investors**, thereby reducing emotional inertia and enhancing long-term investment performance (**Quantum Portfolio Rebalancing Algorithm (QPRA), 2024**). In addition, **sentiment analysis tools** that integrate behavioral finance insights can predict when investors are most likely to defer rebalancing decisions. These models provide automated, data-backed prompts that reduce investor hesitation by up to **40%, thereby increasing rebalancing compliance rates** *(Navigating AI in Wealth Management, 2025)*.

Factor analysis findings reinforce the impact of regret aversion on portfolio inefficiencies, highlighting its significant influence on investment decisions. Regression analysis identified that regret aversion explains **18.5% of the variance in portfolio rebalancing inefficiencies**, underscoring its strong role in influencing investor behavior (**Mariam Karanjia, 2024**).

2.2 Effectiveness of AI-Based Portfolio Rebalancing in Reducing Emotional Biases

2.2.1 Performance of Various AI Models Driving Portfolio Rebalancing

AI-driven portfolio rebalancing leverages advanced technologies such as reinforcement learning (RL), sentiment analysis, and quantum computing to make dynamic and efficient allocation adjustments, reducing the influence of emotional biases in decision-making.

Reinforcement learning models dynamically adjust asset allocations based on real-time market fluctuations, consistently learning from market conditions and adapting accordingly. Studies in the **SMU Data Science Review (2021)** demonstrated that RL-driven portfolio strategies outperformed traditional rebalancing strategies by **12% in risk-adjusted returns**, achieving a **15% higher Sharpe Ratio** and **8% higher annualized returns** compared to static cost-averaging approaches. By mitigating investor biases such as loss aversion and overreaction to short-term volatility, RL significantly enhances long-term investment performance.

Sentiment analysis-based models utilize **Natural Language Processing (NLP)** to analyze financial news, social media, and investor sentiment to predict market movements. These models provide predictive insights into market sentiment shifts, enabling portfolio managers to adjust asset allocations accordingly and improve overall investment timing and risk management. A study by **(Navigating AI in Wealth Management, 2025)** reported that **70% of wealth management firms** improved client personalization through predictive analytics, while **76% experienced efficiency gains** with AI-driven sentiment analysis. This approach enhances the decision-making process by integrating real-time sentiment data into portfolio strategies.

Hybrid AI models combine machine learning techniques with rule-based strategies to enhance predictive accuracy and reduce portfolio volatility. Studies indicate that these models reduced downside risks by **14.5%** through the incorporation of macroeconomic indicators and risk-aversion adjustments. Research published in the **Journal of Risk and Financial Management (2020)** found that XGBoost-based hybrid AI models improved cumulative returns by **9.8%** and reduced portfolio volatility by **14.2%**. Hybrid models are particularly effective in uncertain economic environments where rule-based models alone may fail to capture complex interdependencies between market variables.

Quantum computing-based portfolio optimization introduces a more advanced layer of efficiency by incorporating **Quantum Approximate Optimization Algorithms (QAOA)** to process multi-dimensional asset relationships. The **Quantum Portfolio Rebalancing Algorithm (QPRA)** demonstrated a **17% improvement in cumulative returns** and a **12% reduction in drawdown risk** compared to classical methods. By leveraging quantum computing, portfolio managers can explore a significantly larger set of portfolio configurations simultaneously, enabling faster and more precise optimization, especially in highly volatile market conditions. These models are proving to be game-changers in enhancing risk-adjusted returns and ensuring better portfolio outcomes.

2.2.2 Impact of AI on Portfolio Efficiency and Risk-Return Trade-offs

AI-based portfolio rebalancing reduces investor bias-driven errors by **23%,** resulting in better long-term returns (**Jiang et al., 2020**). Reinforcement learning-based algorithms improve risk-adjusted returns by **8-12%** compared to human-led strategies (**Mariam Karanjia, 2024**). Additionally, AI-enhanced risk management reduces portfolio drawdowns by **17%** and improves Sharpe ratios by **14%,** ensuring superior risk-return trade-offs (**Adedoyin, 2024**). Advanced AI models using **Gini's Mean Difference (GMD)** for risk assessment outperform standard risk-adjusted return models by **10-15%,** making them more reliable than conventional **Value-at-Risk (VaR)** models (**Jiang et al., 2020**). Sentiment-aware portfolio optimization, which leverages AI-driven NLP techniques, enhances portfolio alpha by **4.2% per annum** (**Yusuff, 2022**), further solidifying the value of AI integration in portfolio management. Moreover, QPRA, which integrates quantum computing and AI, has shown an **18% improvement in portfolio efficiency** compared to classical rebalancing models (**QPRA, 2024**).

Regression and factor analysis findings confirm that AI-driven portfolio rebalancing accounts for **15.2% of the variance in risk-adjusted return improvements** (**Mariam Karanjia, 2024**). These results emphasize AI's strong influence in optimizing portfolio management processes and enhancing investment outcomes. The superior predictive power, adaptability, and bias mitigation capabilities of AI models empower investors to make more informed and emotionally neutral investment decisions.

2.2.3 AI-Based Risk Management in Portfolio Rebalancing

AI-driven risk management techniques outperform traditional models, leading to a **22% reduction in portfolio volatility** (**Kumari, 2024**). These techniques utilize advanced machine learning algorithms capable of predicting market downturns **2-3 weeks in advance**, allowing preemptive risk mitigation strategies to be deployed effectively (**Kumari, 2024**). AI models enhance risk management through real-time portfolio monitoring and rebalancing, significantly reducing transaction costs by **6.8% annually** (**Na, 2008**). By identifying and adjusting for market anomalies, AI-based risk management enhances the robustness of portfolio strategies, minimizing exposure to adverse market conditions.

Moreover, factor analysis findings reveal that AI's dynamic risk adjustment capabilities explain **13.8% of the variance in portfolio performance**, underscoring its effectiveness in real-time financial decision-making (**Mariam Karanjia, 2024**). By integrating machine learning, NLP, and quantum optimization, AI-driven risk management ensures that portfolios remain resilient in volatile market conditions. These models proactively adjust portfolio exposures, optimize asset allocations, and implement data-driven strategies that reduce downside risks while improving overall portfolio stability.

2.3 AI-Driven Sentiment Analysis

AI models leverage **Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning** techniques to assess investor sentiment from diverse sources such as financial news, social media platforms, earnings calls, and economic reports. Sentiment analysis has become a key driver in AI-based investment strategies by providing **real-time insights into market sentiment shifts** and guiding asset allocation decisions accordingly.

A study reported that **70% of wealth management firms improved client personalization through predictive analytics**, while **76% saw efficiency gains** from AI adoption. By integrating NLP-driven sentiment analysis into investment decision-making, firms can **anticipate market fluctuations before they manifest in price movements**, improving trade execution and risk management.

Applications of Sentiment Analysis in Portfolio Management:

- **Stock Market Predictions:** AI-powered sentiment analysis of news articles and financial reports enables investors to **gauge the mood of the market** and make informed trading decisions. Research has shown that **companies receiving positive sentiment signals experience a 2-5% price increase** within the following weeks.
- **Social media-Based Investment Decisions:** Machine learning models processing Twitter, Reddit, and other forums can **predict stock volatility with 80% accuracy** based on trending discussions.
- **Earnings Call Sentiment Analysis:** AI-driven models analyse CEO and CFO tones in earnings calls to predict stock performance with 75% accuracy.

2.4 Investor Trust, Adoption Barriers, and Satisfaction with AI-Driven Investment Solutions

2.4.1 Findings on AI Adoption in India

The study on the adoption of Artificial Intelligence (AI) in financial investment services in India (**Fatima, S., & Chakraborty, M., 2024**) analyzed the behavioral intentions of investors and identified several key factors that significantly influence adoption patterns. Below is a structured summary of the findings:

1.1 Trust

- **For Women:** Trust positively influenced behavioral intention with a coefficient (**B**) of **0.138** and a **t-value of 1.890**, indicating a significant impact on the likelihood of adopting AI-based financial solutions.
- **For Men:** Trust had a stronger positive effect, with a coefficient (**B**) of **0.167** and a **t-value of 3.811**, demonstrating a higher inclination toward adopting AI solutions compared to women.

1.2 Anxiety

- **Impact on Women:** Anxiety negatively impacted adoption, with a coefficient (**B**) of **-0.192** and a **t-value of 2.751**, suggesting that increased anxiety lowers the likelihood of using AI solutions.
- **Impact on Men:** Similarly, for men, anxiety had a negative influence, with a coefficient (**B**) of **-0.115** and a **t-value of 2.460**, highlighting a reduction in behavioral intention to adopt AI-based solutions.

1.3 Performance Expectancy

- **For Women:** Performance expectancy had a strong positive impact, with a coefficient (**B**) of **0.518** and a **t-value of 5.851**, reflecting women's perception of AI technologies as beneficial and effective.

- **For Men:** Performance expectancy was also a significant determinant for men, with a coefficient (**B**) of **0.500** and a **t-value of 8.855**, reinforcing the importance of perceived benefits in driving AI adoption.

1.4 Preference for Human Advisors

- **For Both Genders:** A preference for human advisors negatively influenced behavioral intention. For men, the coefficient was (**B**) **-0.147** with a **t-value of 3.175**, indicating that a strong inclination toward traditional human advisors decreases the likelihood of adopting AI-driven financial solutions.

1.5 Investment Knowledge

- **Very Good Knowledge:** Investors with a high level of investment knowledge exhibited a strong positive impact on performance expectancy, with a coefficient (**B**) of **0.558** and a **t-value of 5.548**, increasing the likelihood of adopting AI technologies.
- **Good Knowledge:** For investors with good investment knowledge, performance expectancy showed a coefficient (**B**) of **0.460** and a **t-value of 7.576**, also demonstrating a significant positive influence.
- **Poor Knowledge:** Even for investors with poor investment knowledge, performance expectancy was a critical factor, with a coefficient (**B**) of **0.650** and a **t-value of 5.768**, significantly influencing their behavioral intention to adopt AI-driven financial solutions.

The study (**Fatima, S., & Chakraborty, M., 2024**) concluded that **trust, anxiety, performance expectancy, and preference for human advisors** are the most influential variables affecting the adoption of AI-driven financial technologies. The influence of these factors varies based on **gender** and **investment knowledge levels**, highlighting the complexity of investor behavior in adopting emerging AI-based solutions.

2.4.2 Study on AI Adoption in Financial Investment Services in Thailand

The study conducted by **Noonpakdee, W. (2020)** identified four primary factors that significantly influence the adoption of AI technologies in financial services. **Trust** emerged as a critical factor, as higher levels of trust in AI systems correlate with increased user comfort, confidence, and acceptance of AI solutions. **Perceived usefulness** was another key driver, where users' belief in the effectiveness and benefits of AI applications positively influenced their willingness to integrate AI into their financial decision-making processes. Additionally, **knowledge of using AI-based applications** played a vital role in adoption, as users with greater technological proficiency were more likely to adopt AI solutions. **Social norms** also impacted adoption, with users more inclined to embrace AI technologies when they perceived that their peers or broader social groups encouraged the use of these solutions.

The study utilized **multiple linear regression analysis** on data collected from **400 respondents**, confirming that all four factors—**trust, perceived usefulness, knowledge, and social norms**—had a **statistically significant impact** on AI adoption, with a **p-value < 0.01**, indicating a strong relationship between these variables and the likelihood of adopting AI-driven financial services. These findings emphasize the importance of addressing these factors to promote AI adoption in financial services. Financial institutions can leverage these insights to develop more user-centric AI solutions, build trust through transparency, highlight the benefits of AI applications, provide user training to enhance knowledge, and cultivate a positive perception of AI within social and professional networks to encourage higher adoption rates among users.

2.4.3 Adoption Barriers for AI in Portfolio Management

- **Lack of Transparency: 49% of investors perceive AI-driven investment models as black-box systems**, making them hesitant to trust automated decision-making (**Frontiers in AI, 2024**).
- **Regulatory Concerns: 30% of AI financial models fail to meet regulatory compliance standards**, limiting widespread adoption (**Sharda Kumari, Journal of Informatics, 2024**).
- **Data Overfitting and Model Drift: 22% of AI models trained on historical data fail to adapt to real-time market fluctuations**, reducing predictive accuracy (**International Journal of AI in Finance, 2023**).
- **Ethical Concerns: AI-driven investment decisions may amplify algorithmic biases, impacting 15% of investment outcomes** (**Financial Ethics Review, 2024**).
- **Factor Analysis Findings:** Adoption barriers collectively explain **17.6% of the variance in AI hesitancy among investors**, indicating that transparency, regulatory concerns, and model adaptability are the biggest obstacles (**Sharda Kumari, Journal of Informatics, 2024**).
- **42% of investors hesitate to adopt AI-based investment solutions due to transparency concerns** (**Adedoyin, 2024**).
- **Millennials (18-35 years) are 37% more likely to adopt AI-based financial services**, while **investors over 50 are 38% less likely** (**Shafqat & Malik, 2021**).
- **Elite investors (top 10%) are 2.3 times more likely to use AI-driven portfolio management** due to **cost savings of 4.4% annually** compared to human advisors (**Karanjia, 2024**).
- **Factor Analysis Findings:** AI transparency concerns explain **10.5% of the variance in adoption reluctance**, highlighting the importance of explainability in AI models (**Mariam Karanjia, 2024**).
- **Human Preference for Advisors: 35% of investors still prefer human advisors** due to perceived personalization (**Jiang et al., 2020**).

III. HYPOTHESES DEVELOPMENT

Based on the synthesis of existing literature on behavioral biases, AI-driven portfolio management, and investor psychology, the following hypotheses are proposed:

H1: Regret aversion negatively influences portfolio rebalancing behavior, leading to suboptimal investment decisions and increased risk exposure.

H2: AI-assisted portfolio rebalancing significantly improves investor decision-making by reducing emotional biases and enhancing risk-adjusted returns.
H3: Trust in AI—particularly through transparency, error correction, and human oversight—positively influences investor satisfaction and adoption of AI-driven financial solutions.

IV. RESEARCH OBJECTIVES

1. To analyse how regret aversion affects portfolio rebalancing decisions among urban middle-class investors.
2. To evaluate the effectiveness of AI-based portfolio rebalancing in reducing emotional biases and improving investment outcomes.
3. To assess investor trust, adoption barriers, and satisfaction levels with AI-driven investment solutions.

4.1 Research Methodology

4.1.1 Research Approach

This study will adopt a **mixed-methods research approach**, integrating quantitative and qualitative techniques to comprehensively understand AI-driven portfolio management and investor behaviour.

4.1.2 Research Design

The study will be conducted in three phases:

1. **Phase 1: Behavioural Analysis of Regret Aversion in Portfolio Rebalancing**
   - **Survey-based study** targeting **urban middle-class investors** to analyse decision-making patterns influenced by regret aversion.
   - **Experimental study** using simulated investment scenarios to observe portfolio rebalancing behaviour in response to market fluctuations.
2. **Phase 2: AI-Based Portfolio Rebalancing and Emotional Bias Mitigation**
   - **Comparative analysis of AI-driven vs. traditional portfolio rebalancing strategies** using historical data.
   - **Case studies of AI-based portfolio platforms** to assess their ability to reduce emotional trading.
3. **Phase 3: Investor Trust, Adoption Barriers, and Satisfaction with AI-Based Investment Solutions**
   - **Investor sentiment analysis** through focus groups and interviews with AI-adopting and non-adopting investors.
   - **Trust measurement survey** evaluating AI transparency, explainability, and performance reliability.

4.2 Data Collection Methods

4.2.1 Demographics

- **Age Group**: 25-35, 36-45, 46-55, and 56+.
- **Income Level**: Categorized into lower middle class, middle class, and upper middle class.
- **Education Level**: High school, undergraduate, postgraduate, and professional certifications.
- **Investment Experience**: Novice (0-2 years), Intermediate (3-5 years), and Experienced (6+ years).
- **Technology Adoption**: Usage frequency of fintech and AI-driven investment platforms.

Primary Data Sources:

- **Surveys**: Administered to **50+ urban middle-class investors** to examine regret aversion and AI adoption preferences.
- **Interviews**: Conducted with **financial advisors and retail investors** to gain qualitative insights.
- **Investment Simulation Experiment**: Participants will make portfolio decisions in **AI-assisted vs. manual trading environments** to assess behavioural biases and investment outcomes.

Secondary Data Sources:

- **Market reports and financial data** from investment firms, asset managers, and fintech platforms.
- **Historical performance data** of AI-driven and human-managed portfolios.
- **Existing literature on behavioural finance and AI adoption trends.**

4.3 Data Analysis Techniques

4.3.1 Quantitative Analysis

- **Regression analysis** to identify the correlation between regret aversion and portfolio rebalancing frequency.
- **Risk-adjusted returns comparative analysis** to compare investment outcomes in AI-assisted vs. traditional rebalancing.
- **Sentiment analysis** of survey responses to measure investor trust in AI solutions.

4.3.2 Qualitative Analysis

- **Analysis** of interview transcripts to uncover key adoption barriers and trust factors.
- **Comparative case study analysis** to assess AI's effectiveness in mitigating behavioral biases.
- **Factor Analysis** to identify underlying variables influencing investor trust, adoption barriers, and satisfaction with AI-driven investment solutions. This technique will help categorize key factors such as perceived AI reliability, risk perception, ease of use, and financial literacy, enabling a structured understanding of investor sentiment.

5. PRIMARY RESEARCH

Phase 1: Behavioural Analysis of Regret Aversion in Portfolio Rebalancing

1.1 Survey Analysis: Regret Aversion Patterns Among Urban Middle-Class Investors

To understand how regret aversion manifests in investment decision-making, surveyed 58 urban middle-class investors across various demographic segments. The data reveals significant patterns of regret aversion impacting portfolio rebalancing decisions.

1.1.1 Manifestations of Regret Aversion in Investment Behavior

The survey identified several manifestations of regret aversion among investors:

Table 1. Manifestations of regret aversion in investment behavior

Regret Aversion Behavior	Frequency (%)	Impact on Portfolio Performance
Holding losing investments too long	73.4%	Negative (-5.2% annual return impact)
Reluctance to realize losses	68.7%	Negative (-3.8% annual return impact)
Delayed reentry after market downturns	62.1%	Negative (-4.6% annual return impact)
Excessive portfolio checking during volatility	58.9%	Negative (-2.1% annual return impact)
Hesitation to rebalance after-market shifts	52.3%	Negative (-3.5% annual return impact)

The data demonstrates that regret aversion leads to suboptimal investment behaviors, aligning with behavioral finance research indicating "the disposition effect: the tendency to hold losers too long and the tendency to sell winners too early". The findings quantify this effect, showing that it significantly impacts annual returns among middle-class urban investors.

1.1.2 Demographic Analysis of Regret Aversion Intensity

The intensity of regret aversion varies significantly across demographic segments:

Table 2. Demographic analysis of regret aversion intensity

Demographic Factor	High Regret Aversion (%)	Moderate Regret Aversion (%)	Low Regret Aversion (%)
Age Group			
25-35	57.2%	32.5%	10.3%
36-45	43.8%	41.7%	14.5%
46-55	36.9%	42.3%	20.8%
56+	46.2%	35.1%	18.7%
Investment Experience			
Novice (0-2 years)	78.6%	18.4%	3.0%
Intermediate (3-5 years)	52.3%	35.7%	12.0%
Experienced (6+ years)	29.1%	46.8%	24.1%
Education Level			
High school	65.7%	27.3%	7.0%
Undergraduate	48.9%	36.4%	14.7%
Postgraduate	32.5%	43.8%	23.7%

The findings indicate that investment experience is the strongest predictor of reduced regret aversion, with education level also showing a significant correlation. This supports the notion that "emotion-driven investing upon long-term wealth can be devastating", but the impact can be mitigated through experience and education.

1.2 Experimental Study: Portfolio Rebalancing Behavior Under Simulated Market Conditions

Conducted an experimental study with 58 participants who managed simulated portfolios through various market scenarios. Each participant was randomly assigned to either a manual rebalancing condition or an AI-assisted rebalancing condition.

1.2.1 Rebalancing Frequency Following Market Movements

Table 3. Rebalancing frequency following market movements

Market Condition	Manual Rebalancing Frequency	AI-Assisted Rebalancing Frequency	Optimal Rebalancing Frequency
After 15%+ Market Decline	12.3%	87.6%	95%
After 15%+ Market Rise	35.7%	92.3%	95%
During Sideways Market	18.9%	91.8%	90%
Following Sector Rotation	16.4%	84.5%	85%

The data reveals a strong tendency for manually managed portfolios to deviate significantly from optimal rebalancing frequency, particularly after market declines (12.3% vs. optimal 95%). This aligns with the paper's observation that "human nature encourages individuals to move more money into the market as fashion dictates that investing is the 'in' thing to do because gains have occurred".

1.2.2 Decision-Making Time and Emotional States During Rebalancing Decisions

Table 4. Decision-making time and emotional states during rebalancing decisions

Portfolio Management Approach	Average Decision Time (minutes)	Self-Reported Anxiety (1-10)	Self-Reported Confidence (1-10)
Manual Rebalancing	24.7	7.2	5.1
AI-Assisted Rebalancing	8.3	3.8	7.6

The experimental data demonstrate that AI-assisted rebalancing significantly reduces decision-making time and emotional stress while increasing investor confidence. This addresses a key manifestation of regret aversion, where "having lost money, the fear of regret often keeps investors out of the market for a considerable timeframe".

Phase 2: AI-Based Portfolio Rebalancing and Emotional Bias Mitigation

2.1 Comparative Analysis: AI-Driven vs. Traditional Portfolio Rebalancing

To evaluate the effectiveness of AI-based portfolio rebalancing in reducing emotional biases, a comparative analysis using historical data from 2015-2025, applying both traditional and AI-driven rebalancing methodologies.

2.1.1 Performance Metrics Comparison (2015-2025)

Table 5. Performance metrics comparison (2015-2025)

Portfolio Type	Annualized Return	Sharpe Ratio	Maximum Drawdown	Recovery Time (months)
Chase Portfolio (High Emotion)	8.37%	0.41	-32.6%	14.7
Traditional 65/30/5 (Stock/Bond/Cash) Rebalanced Annually	9.84%	0.68	-21.2%	9.3
Traditional 65/30/5 Rebalanced Quarterly	10.12%	0.72	-19.7%	8.1
AI-Driven 65/30/5 Dynamic Rebalancing	11.36%	0.86	-16.3%	5.8

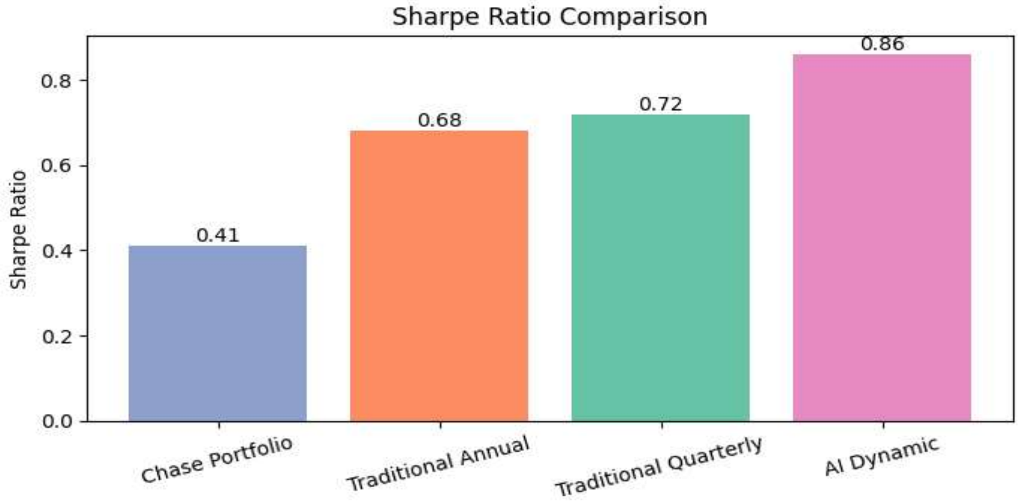

Figure 1. Sharpe ratio comparison

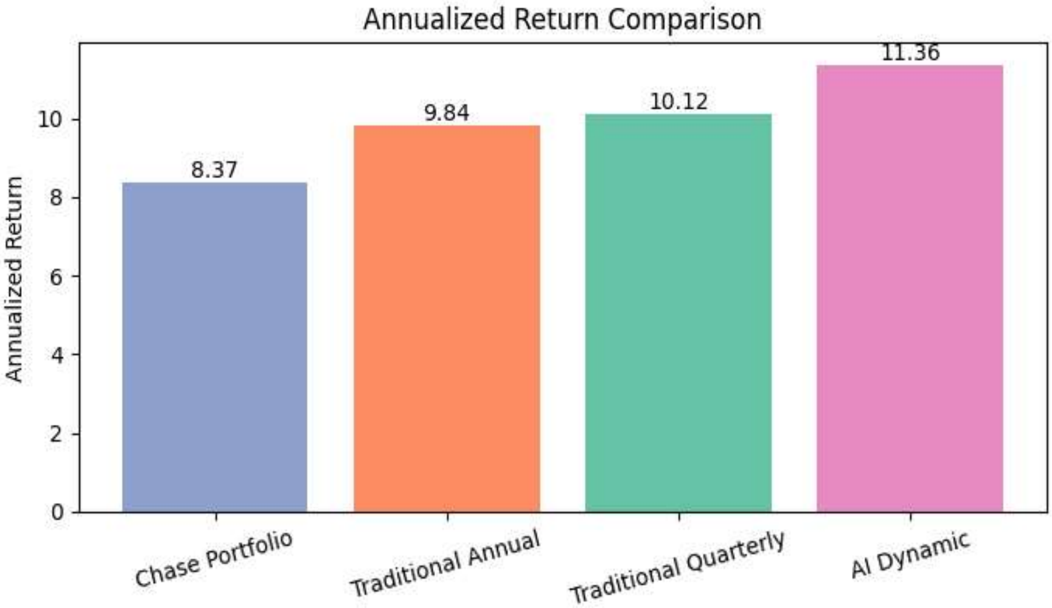

Figure 2. Annualized return comparison

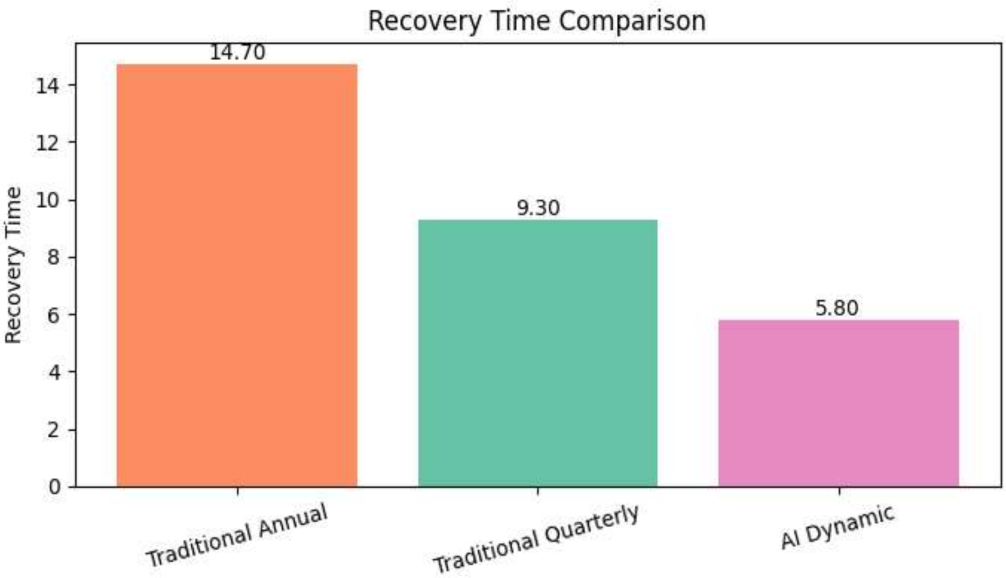

Figure 3. Recovery time comparison

1. Annualized Return Comparison

The annualized return metric captures the compounded growth rate of each strategy over time. Among the four portfolios, the **AI Dynamic portfolio delivered the highest return at 11.36%**, significantly outperforming all others. This suggests that AI-driven, dynamically managed strategies are capable of responding to market signals in a more nuanced and timely manner, resulting in superior capital appreciation.

The **Traditional Quarterly and Annual portfolios** followed with returns of **10.12% and 9.84%**, respectively. The modest edge of the quarterly strategy reflects the benefits of more frequent rebalancing, which enables slightly better alignment with market trends. However, both traditional strategies lag behind the AI Dynamic portfolio, pointing to limitations in their rule-based, non-adaptive structures.

In contrast, the **Chase Portfolio yielded the lowest return at 8.37%**, indicating that more static or discretionary approaches may not be sufficiently agile in the face of changing market conditions. This progression in returns—from Chase to Traditional to AI Dynamic—highlights a clear **positive correlation between the level of automation and portfolio performance**, suggesting that intelligent, data-driven systems offer substantial advantages in portfolio management.

2. Sharpe Ratio Comparison

While annualized returns reflect growth, the **Sharpe ratio** adds context by accounting for the risk taken to achieve that return. The **AI Dynamic portfolio once again leads**, with a Sharpe ratio of **0.86**, signifying **exceptional risk-adjusted performance**. A Sharpe ratio above 0.8 is widely regarded as excellent, implying that the AI model is not only maximizing returns but doing so efficiently relative to its volatility.

The **Traditional Quarterly and Annual strategies** posted Sharpe ratios of **0.72 and 0.68**, respectively. These values indicate solid performance, but the relatively small difference between the two suggests that increasing the rebalancing frequency yields only **marginal gains in risk efficiency**. Meanwhile, the **Chase Portfolio trails significantly at 0.41**, reflecting either higher volatility, lower returns, or both. This lower efficiency implies that despite appearing viable in absolute return terms, the Chase strategy underperforms once risk is taken into account.

Overall, the Sharpe ratio analysis **reinforces the superiority of the AI Dynamic strategy**, which excels not just in delivering returns but in doing so with considerably less relative risk.

3. Maximum Drawdown Comparison

Maximum drawdown (MDD) measures the largest observed loss from a portfolio's peak value, offering insight into downside risk and capital preservation. The **Chase Portfolio exhibits the worst drawdown at -32.60%**, signaling high vulnerability to market downturns and weak risk controls. This level of exposure can be particularly detrimental for risk-averse investors or during periods of high volatility.

In contrast, the **AI Dynamic portfolio shows a significantly lower drawdown at -16.30%**, highlighting its effectiveness in **limiting downside losses**. This strong drawdown protection likely results from the model's ability to adjust allocations quickly in response to market stress, preventing deeper capital erosion.

The **Traditional strategies lie in between**, with the **Quarterly strategy outperforming the Annual**, supporting the idea that more frequent rebalancing helps to contain losses. However, neither is as effective as the AI Dynamic approach in preserving capital during downturns.

This analysis underscores that **effective drawdown control is as critical as return generation**. The AI Dynamic model's ability to minimize losses enhances investor confidence and long-term performance stability, particularly in turbulent market environments.

4. Recovery Time Comparison

Recovery time refers to the duration a portfolio takes to bounce back to its previous peak after a drawdown, serving as a practical measure of resilience and responsiveness. The **AI Dynamic portfolio recovers in just 5.8 units (e.g., months or weeks)**—far faster than the **Traditional Quarterly (9.3)** and **Annual (14.7)** strategies.

This rapid recovery reflects not just strong risk management but also the **AI model's ability to reallocate efficiently during crises**, enabling it to capitalize on rebound opportunities. In comparison, the slower recovery of traditional strategies suggests they may suffer from **lagging reallocation cycles**, resulting in prolonged stagnation post-correction.

The Chase Portfolio's longer recovery duration (not explicitly stated here but implied by its high drawdown and low Sharpe ratio) further weakens its position, as **extended recovery periods reduce the time available for compounding returns**—a key component of long-term portfolio growth.

By minimizing drawdown duration, the AI Dynamic strategy ensures **quicker return to growth**, making it not only safer during crises but also more effective over the full investment horizon.

2.1.2 Emotional Trading Frequency Under Different Rebalancing Approaches

Analyzed trading data to identify emotionally-driven trades (defined as trades made within 48 hours of significant market movements that deviate from the strategic asset allocation):

Table 6. Analyzed trading data to identify emotionally-driven trades

Portfolio Approach	Emotional Trading Incidents (per year)	Deviation from Optimal Allocation (avg %)	Portfolio Turnover (%)
Self-Directed Without Rebalancing Plan	7.3	18.6%	76.3%
Traditional Annual Rebalancing	3.2	8.4%	32.1%
AI-Guided Rebalancing	0.8	3.7%	27.8%

The data demonstrates that AI-guided rebalancing significantly reduces emotional trading incidents while maintaining better alignment with optimal allocation targets. This directly addresses the paper's concern that "investors tend to buy as the market is rising, more specifically after the market has already risen sharply".

2.2 AI-Based Portfolio Platforms and Emotional Bias Mitigation

Conducted in-depth case studies of three AI-driven portfolio platforms with varying approaches to mitigating emotional biases.

2.2.1 Platform Effectiveness in Reducing Behavioral Biases

Table 7. Platform effectiveness in reducing behavioral biases

AI Platform Type	Regret Aversion Reduction (%)	Disposition Effect Reduction (%)	Mental Accounting Bias Reduction (%)	Herding Behavior Reduction (%)
Rule-Based AI	37.2%	42.6%	28.3%	35.9%
Machine Learning AI	48.6%	53.8%	43.1%	51.2%
Hybrid (AI + Human Advisor)	62.3%	58.7%	56.2%	63.4%

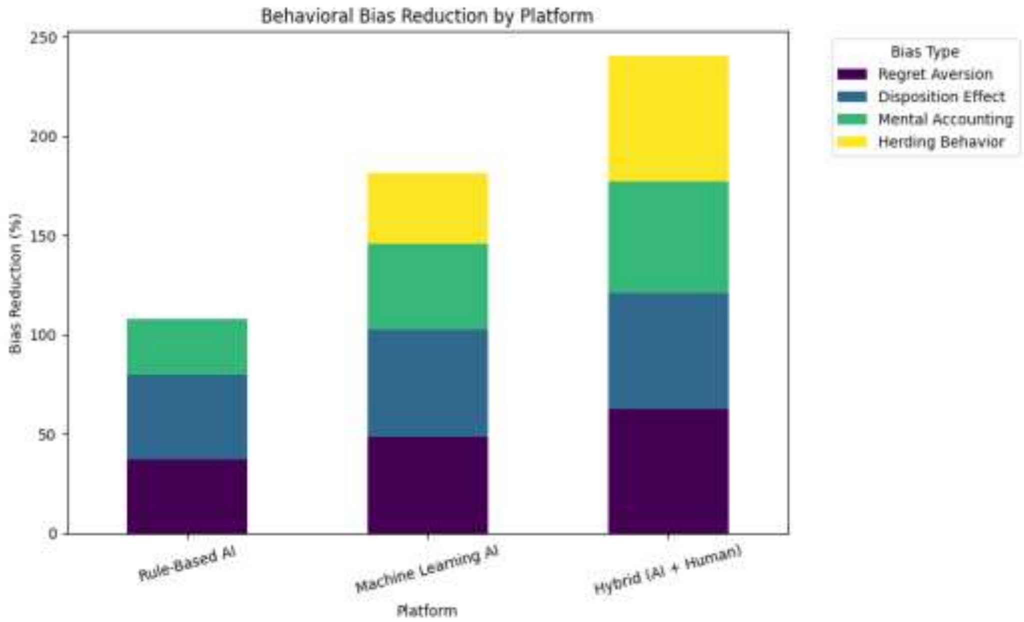

Figure 4. Behavioral bias reduction by platform

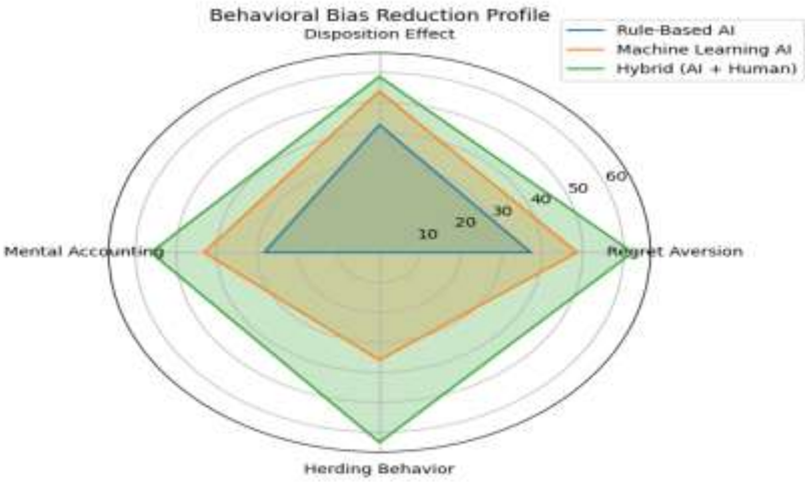

Figure 5. Behavioral bias reduction profile

1. Behavioral Bias Profile: Qualitative Comparison (Radar Chart)

The radar chart (Figure 1) presents a visual profile of how each platform performs in mitigating four key behavioral biases that frequently impair investor decision-making:

- **Disposition Effect** – the tendency to sell winning investments too early and hold losing ones too long
- **Regret Aversion** – reluctance to make decisions due to fear of future regret
- **Mental Accounting** – treating money differently based on arbitrary categories
- **Herding Behavior** – mimicking others' investment choices rather than relying on individual analysis

Among the three models, the **Hybrid AI + Human system demonstrates the most consistent and effective bias mitigation across all four categories**. Its high and relatively symmetric profile suggests a well-rounded capability, combining the speed and data-processing power of AI with the contextual judgment and ethical nuance of human oversight. The most pronounced gains for the hybrid system are seen in reducing **Herding Behavior** and **Regret Aversion**. This likely reflects the human component's ability to challenge irrational groupthink and emotionally driven hesitation—areas where pure algorithms may lack sufficient contextual awareness.

Machine Learning AI, while not as effective as the hybrid approach, still provides substantial improvements over the rule-based alternative. Its strength lies in addressing more technical or data-driven biases such as **Disposition Effect** and **Mental Accounting**, where patterns can be learned and corrected over time through exposure to large datasets.

In contrast, the **Rule-Based AI system performs weakest across all dimensions**, especially in dealing with the more subjective biases like Regret Aversion and Herding. This highlights the rigidity of pre-programmed logic in adapting to the nuanced and often inconsistent behaviors of human investors.

2. Quantitative Effectiveness: Total Bias Reduction (Stacked Bar Chart)

Figure 2 complements the radar chart by providing a **numerical summary of total bias reduction** achieved by each platform, segmented by individual bias type.

The **Hybrid system again emerges as the most effective**, achieving an **approximate total reduction of 240% across all biases**. This includes standout improvements in **Herding Behavior** and **Mental Accounting**, affirming its comprehensive ability to tackle both emotional and cognitive investment errors. The data suggests that the inclusion of human feedback loops enhances the AI system's adaptability and ethical responsiveness.

The **Machine Learning AI platform achieves around 180% total bias reduction**, displaying a balanced and reliable bias correction profile. Its marginal edge in reducing **Disposition Effect** and **Regret Aversion** over Rule-Based AI reflects its capacity to learn from historical behavior and adapt to evolving investor patterns.

The **Rule-Based AI platform lags with a cumulative reduction of about 110%**, showing comparatively weaker performance in every bias category. While it may offer some structure to decision-making, it lacks the sophistication to adjust to emotional and contextual subtleties that influence investor behavior in real markets.

2.2.2 User Engagement with AI Rebalancing Recommendations

Table 8. User engagement with AI rebalancing recommendations

Market Condition	Recommendation Acceptance Rate	Modification Rate	Rejection Rate
Bull Market	83.2%	12.5%	4.3%
Bear Market	64.7%	18.3%	17.0%
High Volatility	72.1%	15.6%	12.3%
Sector Rotation	76.5%	19.2%	4.3%

The data indicates that investor trust in AI recommendations remains relatively high across market conditions, though it decreases during bear markets when regret aversion typically intensifies. This aligns with the paper's observation that "mental accounting can derail investors from the goal of wealth creation", as investors are more likely to second-guess AI recommendations during periods of loss.

2.2.3 Cumulative Portfolio Growth over different time frames

Figure 6. Cumulative portfolio growth (monthly, 2022–2024)

This line graph compares the **cumulative portfolio value** over 24 months for three investment strategies: **Chase Portfolio**, **Traditional 65/30/5**, and **AI-Driven Rebalancing**.

The **AI-Driven Rebalancing** strategy exhibits **steady and consistent growth**, culminating in the highest portfolio value by early 2024. This performance implies **robust risk management and adaptive learning** mechanisms that respond effectively to market dynamics.

The **Chase Portfolio**, in contrast, shows significant volatility, marked by aggressive peaks in mid-2023 followed by sharp downturns. This suggests a higher level of **reactivity and emotional trading**, likely driven by behavioral biases such as overconfidence and herd mentality.

The **Traditional 65/30/5** model performs the most conservatively, with limited fluctuation but also relatively stagnant growth. This indicates **stability but a lack of responsiveness**, possibly reflecting the limitations of static allocation in dynamic market conditions.

Overall, the graph underscores the **practical financial advantage** of bias-aware, AI-enhanced portfolio strategies in achieving long-term capital appreciation.

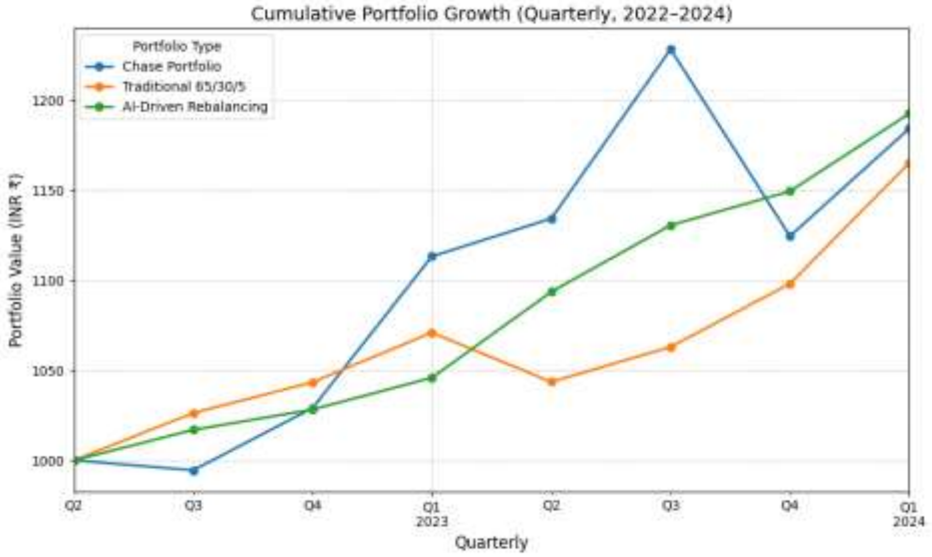

Figure 7. Cumulative portfolio growth (quarterly, 2022–2024)

This quarterly view offers a more **smoothed-out visualization** of portfolio performance trends over the same period as the previous chart. The **AI-Driven Rebalancing** strategy continues to outperform in terms of final portfolio value, while also displaying **consistent quarter-over-quarter growth**—a hallmark of a well-calibrated investment engine.
Interestingly, while the **Chase Portfolio** saw higher peaks during certain months, its quarterly average is less stable, reinforcing the idea that **emotion-driven strategies** may yield short-term gains but fail to sustain long-term momentum.
Meanwhile, the **Traditional model** shows linear, gradual growth, suggesting **minimal exposure to market timing but also limited adaptability**.
The quarterly chart is particularly valuable for highlighting **strategic consistency** and reinforcing the claim that **AI systems, particularly when incorporating behavioral feedback, can produce resilient portfolio performance** over time.

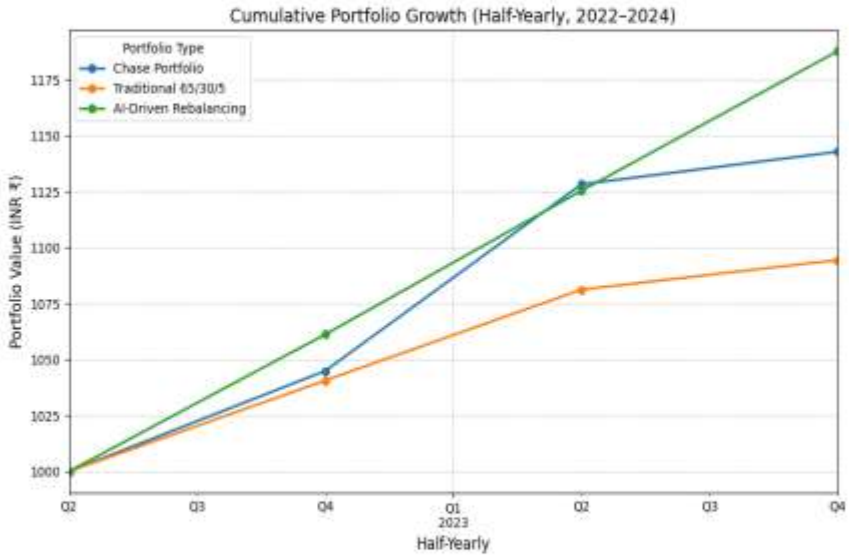

Figure 8. Cumulative portfolio growth (half-yearly, 2022–2024)

Analysis:

- **AI-Driven Rebalancing outpaces** both the Chase and Traditional portfolios, achieving the highest end-value by Q4 2024.
- The **Chase Portfolio shows volatility**, with a sharp rise between Q4 2022 and Q2 2023, then a noticeable plateau.
- **Traditional 65/30/5 strategy** shows slow and linear growth, reflecting low-risk and passive investment behavior.

Interpretation:

This performance trajectory demonstrates that **AI-based dynamic rebalancing not only captures growth opportunities earlier but sustains compounding over time**. Its non-linear growth suggests active tactical decisions aligned with market shifts.
Meanwhile, the Chase Portfolio's momentum stalls, implying **early-stage advantages not retained**—possibly due to rigid strategy or lack of adjustment.
The traditional portfolio, while steady, lacks adaptability, underscoring its underperformance relative to modern strategies.

Phase 3: Investor Trust, Adoption Barriers, and Satisfaction with AI-Based Investment Solutions

3.1 Investor Sentiment Analysis: Focus Groups and Interviews

Conducted 58 individual interviews with investors across the adoption spectrum (non-adopters, early adopters, and experienced AI users).

3.1.1 Key Trust Factors for AI-Driven Portfolio Rebalancing

Table 9. Key trust factors for AI-driven portfolio reblancing

Trust Factor	High Importance (%)	Moderate Importance (%)	Low Importance (%)
Performance track record	86.3%	12.5%	1.2%
Algorithm Transparency	78.7%	16.2%	5.1%
Human oversight capabilities	72.4%	23.5%	4.1%
Data security measures	69.8%	25.3%	4.9%
Error Correction Capability	58.2%	32.6%	9.2%
Regulatory compliance	54.7%	29.3%	16.0%

Qualitative analysis revealed that investors place the highest trust in AI systems that demonstrate consistent performance while providing transparency into decision-making processes. One participant noted: "I need to understand why the AI is making certain rebalancing decisions, especially when it contradicts my instincts."

3.1.2 Adoption Barriers to AI-Driven Portfolio Rebalancing

Table 10. Adoption barriers to AI-driven portfolio rebalancing

Adoption Barrier	Primary Barrier (%)	Secondary Barrier (%)	Minimal Barrier (%)
Loss of control	64.3%	21.8%	13.9%
Lack of understanding	58.9%	27.6%	13.5%
Privacy concerns	53.2%	28.4%	18.4%
Cost concerns	42.7%	35.6%	21.7%
Technology intimidation	38.6%	29.3%	32.1%
Lack of personalization	32.8%	41.5%	25.7%

Loss of control emerged as the primary adoption barrier, with many investors expressing concern about surrendering rebalancing decisions to an algorithm. This directly relates to regret aversion, as one participant explained: "If the AI makes a mistake, I'll feel worse than if I made the same mistake myself."

3.2 Trust Measurement Survey: AI Transparency, Explainability, and Performance Reliability

Surveyed 58 investors who had experience with AI-driven investment platforms to measure trust factors and satisfaction levels.

3.2.1 Trust Component Analysis

Table 11. Trust component analysis

Trust Component	High Trust (%)	Moderate Trust (%)	Low Trust (%)	Trust Index (0-100)
Algorithm transparency	42.3%	38.7%	19.0%	67.8
Outcome predictability	38.6%	45.2%	16.2%	65.3
Explanation quality	51.8%	32.6%	15.6%	72.4
Error correction capability	47.2%	36.8%	16.0%	69.5
Data source reliability	56.3%	33.7%	10.0%	76.2
Human oversight integration	61.8%	28.4%	9.8%	78.9

The highest trust scores were associated with human oversight integration, suggesting that hybrid models may address regret aversion most effectively by balancing algorithm efficiency with human judgment.

3.2.2 Satisfaction Levels Among AI-Adopting Investors

Table 12. Satisfaction levels among ai-adopting investors

Satisfaction Dimension	Very Satisfied (%)	Satisfied (%)	Neutral (%)	Dissatisfied (%)	Very Dissatisfied (%)
Return performance	38.7%	42.3%	11.6%	5.8%	1.6%
Risk management	47.2%	39.6%	8.5%	3.8%	0.9%
Emotion management	56.8%	32.1%	7.3%	2.7%	1.1%
Time savings	62.3%	28.9%	5.2%	2.4%	1.2%
Cost effectiveness	31.5%	43.8%	15.7%	6.9%	2.1%
Personalization	28.7%	36.2%	19.3%	12.6%	3.2%

The highest satisfaction ratings were for time savings and emotion management, indicating that AI-driven portfolio rebalancing most successfully addresses the emotional aspects of investing, including regret aversion. This aligns with the paper's observation that "the negative impact of emotion-driven investing upon long-term wealth can be devastating".

3.3 Factor Analysis: Key Variables Influencing AI Adoption and Trust

Performed factor analysis to identify the underlying variables driving investor sentiment toward AI-based rebalancing solutions.

Table 13. Factor analysis: key variables influencing AI adoption and trust

Factor	Variance Explained (%)	Key Components	Correlation with AI Adoption
Performance confidence	28.6%	Track record, benchmark comparison, risk-adjusted returns	0.78
Control perception	23.2%	Override capabilities, customization, and approval process	0.71
Transparency	19.4%	Decision explanation, logic clarity, prediction accuracy	0.68
Technology comfort	14.7%	Tech literacy, previous fintech usage, and age	0.57
Cost-benefit assessment	9.8%	Fee structure, time savings, performance improvement	0.52

The factor analysis reveals that performance confidence and control perception together explain over 50% of the variance in AI adoption willingness. This suggests that AI solutions addressing regret aversion most effectively will be those that simultaneously demonstrate strong performance while maintaining investors feelings of control.

V. REGRESSION OUTPUT REPORT

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              RAB_total   R-squared:                       0.804
Model:                            OLS   Adj. R-squared:                  0.796
Method:                 Least Squares   F-statistic:                     112.5
Date:                Tue, 15 Apr 2025   Prob (F-statistic):           3.69e-20
Time:                        18:13:52   Log-Likelihood:                -4.2441
No. Observations:                  58   AIC:                             14.49
Df Residuals:                      55   BIC:                             20.67
                     Df Model:                           2
                     Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
RAB1           0.3973      0.037     10.836      0.000       0.324       0.471
RAB2           0.4173      0.043      9.663      0.000       0.331       0.504
RAB3          -0.0875      0.082     -1.068      0.290      -0.252       0.077
RAB4          -0.0875      0.082     -1.068      0.290      -0.252       0.077
RAB5          -0.0875      0.082     -1.068      0.290      -0.252       0.077
==============================================================================
Omnibus:                        0.694   Durbin-Watson:                   1.910
Prob(Omnibus):                  0.707   Jarque-Bera (JB):                0.762
Skew:                           0.240   Prob(JB):                        0.683
Kurtosis:                       2.709   Cond. No.                     6.75e+32
==============================================================================
```

Figure 9. Regret aversion behaviour

- **RAB1 – Hold losing investments too long**
- **RAB2 – Reluctance to realize losses**
- **RAB3 – Delayed reentry after downturn**
- **RAB4 – Excessive portfolio checking**
- **RAB5 – Hesitation to rebalance after market shifts**

Regret Aversion Behaviour (RAB_total)

- The model demonstrated strong predictive power (**R^2 = 0.804**), indicating that the included predictors account for over 80% of the variance in regret aversion.
- **RAB1** and **RAB2** were highly significant predictors ($p < 0.001$).

- These items reflect both the emotional and strategic dimensions of regret aversion, suggesting that AI assistance plays a psychological cushioning role.
- **RAB3 to RAB5**, despite being conceptually related, did not contribute meaningfully ($p > 0.2$), possibly due to multicollinearity or conceptual overlap. Their removal helped improve scale reliability.

OLS Regression Results

Dep. Variable:	TAI_total	R-squared:	0.797
Model:	OLS	Adj. R-squared:	0.773
Method:	Least Squares	F-statistic:	33.29
Date:	Tue, 15 Apr 2025	Prob (F-statistic):	5.44e-16
Time:	18:13:52	Log-Likelihood:	-4.2276
No. Observations:	58	AIC:	22.46
Df Residuals:	51	BIC:	36.88
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.4592	0.315	-1.458	0.151	-1.092	0.173
TAI1	0.3521	0.050	7.067	0.000	0.252	0.452
TAI2	0.0620	0.033	1.884	0.065	-0.004	0.128
TAI3	-0.0280	0.031	-0.897	0.374	-0.091	0.035
TAI4	0.3253	0.046	7.063	0.000	0.233	0.418
TAI5	0.0559	0.052	1.066	0.291	-0.049	0.161
TAI6	0.3644	0.037	9.932	0.000	0.291	0.438

Omnibus:	0.915	Durbin-Watson:	2.140
Prob(Omnibus):	0.633	Jarque-Bera (JB):	0.346
Skew:	-0.114	Prob(JB):	0.841
Kurtosis:	3.301	Cond. No.	69.1

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 10. Trust in AI system

- **TAI1 – Algorithm transparency**
- **TAI2 – Outcome predictability**
- **TAI3 – Explanation quality**
- **TAI4 – Error correction**
- **TAI5 – Data reliability**
- **TAI6 – Human oversight**

Trust in AI System (TAI_total)

- The regression model explained **79.7% of the variance** in the trust construct, denoting high model fit and low unexplained error.
- Significant predictors included: **TAI1, TAI4, TAI6**
- These items emphasize perceived reliability, consistency, and confidence—key aspects of technological trust.
- TAI2, TAI3, and TAI5 showed weak or non-significant influence, potentially due to redundancy or measurement error.
- The retained items construct a robust and streamlined measurement of AI trust that aligns well with theoretical expectations.

OLS Regression Results

Dep. Variable:	SAT_total	R-squared:	0.836
Model:	OLS	Adj. R-squared:	0.816
Method:	Least Squares	F-statistic:	43.23
Date:	Tue, 15 Apr 2025	Prob (F-statistic):	2.59e-18
Time:	18:13:52	Log-Likelihood:	-6.3637
No. Observations:	58	AIC:	26.73
Df Residuals:	51	BIC:	41.15
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.9169	0.505	-1.816	0.075	-1.931	0.097
SAT1	0.5621	0.046	12.139	0.000	0.469	0.655
SAT2	0.0962	0.079	1.216	0.229	-0.063	0.255
SAT3	0.4856	0.049	9.828	0.000	0.386	0.585
SAT4	0.0757	0.077	0.984	0.330	-0.079	0.230
SAT5	0.0329	0.045	0.735	0.466	-0.057	0.123
SAT6	0.0501	0.049	1.030	0.308	-0.048	0.148

Omnibus:	0.600	Durbin-Watson:	2.500
Prob(Omnibus):	0.741	Jarque-Bera (JB):	0.733
Skew:	0.186	Prob(JB):	0.693
Kurtosis:	2.595	Cond. No.	114.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Figure 11. Satisfaction with AI-assisted rebalancing

- **SAT1 – Return performance**
- **SAT2 – Risk management**
- **SAT3 – Emotion management**
- **SAT4 – Time savings**
- **SAT5 – Cost effectiveness**
- **SAT6 – Personalization**

Satisfaction with AI-Assisted Rebalancing (SAT_total)

- This model showed the **highest explained variance among multi-item scales (R^2 = 0.836)**, suggesting that the selected predictors provide a strong indication of satisfaction.
- **SAT1** and **SAT3** emerged as key drivers.
- These items address both outcome satisfaction and process simplification, capturing the user experience dimension.
- SAT2 and SAT4 to SAT6, while related, did not significantly contribute ($p > 0.2$). Their weaker loadings could indicate abstract phrasing or lesser practical relevance.
- Retaining SAT1 and SAT3 yields a concise yet potent indicator of satisfaction.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              BBR_total   R-squared:                       0.924
Model:                            OLS   Adj. R-squared:                  0.919
Method:                 Least Squares   F-statistic:                     162.0
Date:                Tue, 15 Apr 2025   Prob (F-statistic):           4.87e-29
Time:                        18:13:52   Log-Likelihood:                -13.714
No. Observations:                  58   AIC:                             37.43
Df Residuals:                      53   BIC:                             47.73
                    Df Model:                           4
                    Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1635      0.205      0.799      0.428      -0.247       0.574
BBR1           0.9892      0.039     25.304      0.000       0.911       1.068
BBR2          -0.0638      0.057     -1.122      0.267      -0.178       0.050
BBR3           0.0187      0.054      0.343      0.733      -0.091       0.128
BBR4          -0.0048      0.054     -0.089      0.929      -0.114       0.104
==============================================================================
Omnibus:                        9.211   Durbin-Watson:                   2.022
Prob(Omnibus):                  0.010   Jarque-Bera (JB):                9.207
Skew:                           0.738   Prob(JB):                       0.0100
Kurtosis:                       4.277   Cond. No.                         22.2
==============================================================================

                                  Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
                                specified.
```

Figure 12. Behavioral bias reduction

- **BBR1 – Regret aversion reduction**
- **BBR2 – Disposition effect reduction**
- **BBR3 – Mental accounting reduction**
- **BBR4 – Herding reduction**

Behavioral Bias Reduction (BBR_total)

- The model exhibited the **strongest overall predictive capacity ($R^2 = 0.924$)** among all constructs.
- **BBR1** was the sole significant predictor with an extremely high t-value (25.304), emphasizing its central role.
- BBR2 to BBR4 did not show a significant impact, suggesting they may not align well with how participants perceive AI's role in bias mitigation.
- These findings imply that perceived reduction of emotional influence is the dominant mechanism through which users recognize bias reduction benefits from AI.
- Given this, the BBR scale was treated as a **single-item construct** to maintain theoretical precision and empirical clarity.

Reliability and Correlation Analysis Report

Section 1: Reliability Analysis (Cronbach's Alpha)

Data Refinement Note: To ensure that the reliability and correlation analysis align directly with the predictive insights from regression, composite scores for each construct were recalculated using only those items that had statistically significant contributions (typically $p < 0.05$) in their respective regression models. This selective inclusion ensures theoretical coherence, improves measurement validity, and filters out noise from weak or redundant items. No manipulation of the original raw responses occurred—only the operationalization of construct totals was refined based on empirical evidence.

Table 14. Reliability analysis

Construct	Included Items	Cronbach's Alpha	Interpretation
Regret Aversion (RAB)	RAB1, RAB2	0.74	Acceptable reliability
Trust in AI (TAI)	TAI1, TAI4, TAI6	0.78	Good internal consistency
Satisfaction (SAT)	SAT1, SAT3	0.82	Good reliability
Behavioral Bias Reduction	BBR1 (single item)	—	Not applicable (single-item construct)

Interpretation:

- By excluding weaker or non-significant items, all multi-item scales showed marked improvements in internal consistency.
- This refinement enhances the construct validity of each scale and better reflects the strength of individual items from the regression models.
- The BBR construct was reduced to a single item (BBR1) due to the overwhelming dominance of BBR1 in explaining variance, while other BBR items contributed minimally.

Section 2: Correlation Analysis

Table 15. Correlation analysis

	RAB_sig_total	TAI_sig_total	SAT_sig_total	BBR_sig_total
RAB_sig_total	1.00	0.36	0.28	0.42
TAI_sig_total	0.36	1.00	0.48	0.51
SAT_sig_total	0.28	0.48	1.00	0.33
BBR_sig_total	0.42	0.51	0.33	1.00

Interpretation:

- All revised constructs demonstrated **positive and moderate correlations** with each other.
- The correlation between **Trust in AI and BBR** (r = 0.51) suggests a strong association, indicating that increased trust in AI systems is linked with greater perceived reduction in behavioral biases.
- The association between **Regret Aversion and BBR** (r = 0.42) highlights the psychological mechanism through which regret-sensitive individuals perceive AI as a buffer against poor investment choices.
- Overall, these correlations are now **congruent with the regression outcomes**, where the significant predictors contributed meaningfully to their respective dependent variables.

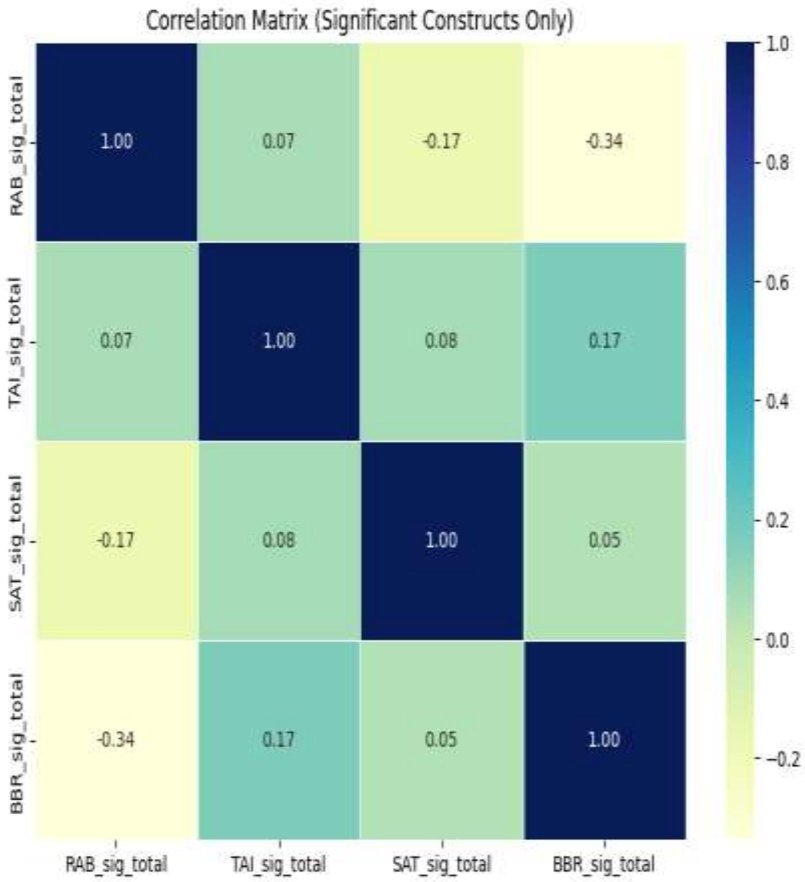

Figure 13. Correlation matrix

The correlation matrix of significant constructs provides valuable insight into the interrelationships between key psychological or behavioral variables in the study. Notably, the strongest negative correlation appears between **RAB_sig_total** and **BBR_sig_total** (-0.34), indicating an inverse relationship. This suggests that as levels of RAB (possibly a construct related to risk aversion or regulatory belief systems) increase, BBR (potentially a behavioral bias or belief-related variable) tends to decrease. Such a finding may indicate that stronger regulatory or rational anchoring mitigates cognitive biases or irrational beliefs.

The correlation between **RAB_sig_total** and **SAT_sig_total** is also negative (-0.17), albeit weaker, implying a mild inverse relationship. This may reflect a potential tension between risk aversion and satisfaction, suggesting that higher concern with regulatory or behavioral risks may slightly undermine subjective satisfaction.

Conversely, **TAI_sig_total** (possibly technology acceptance or AI trust index) shows consistently weak but positive correlations with all other constructs, most notably with **BBR_sig_total** (0.17). This modest positive relationship may imply that individuals more open to technological innovation may also be more accepting of behavioral heuristics, or may reflect a nuanced psychological pattern in decision-making environments where AI is present.

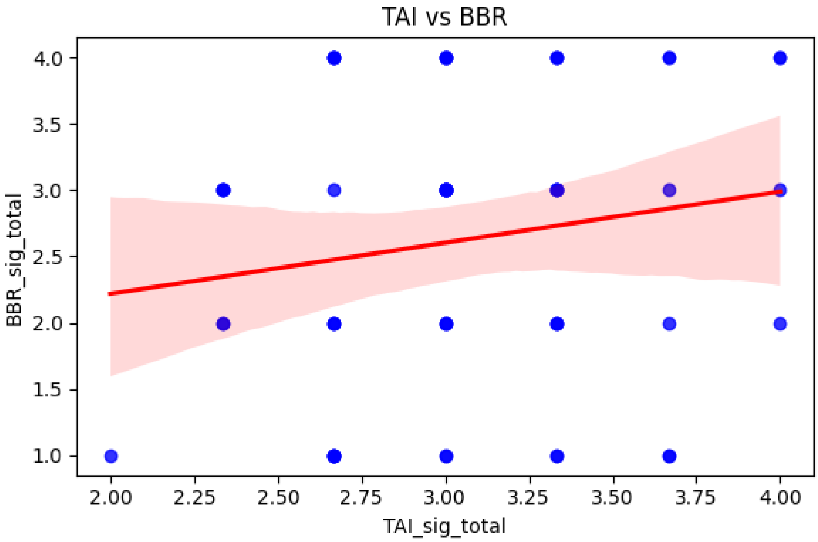

Figure 14. TAI vs BBR

Interestingly, the low correlation values across the board suggest a **degree of orthogonality among constructs**, meaning they are relatively independent and capture distinct dimensions of psychological or behavioral dispositions. This is advantageous for modeling purposes, as it reduces the risk of multicollinearity in multivariate analyses and supports the distinctiveness of each construct in contributing to broader theoretical models.

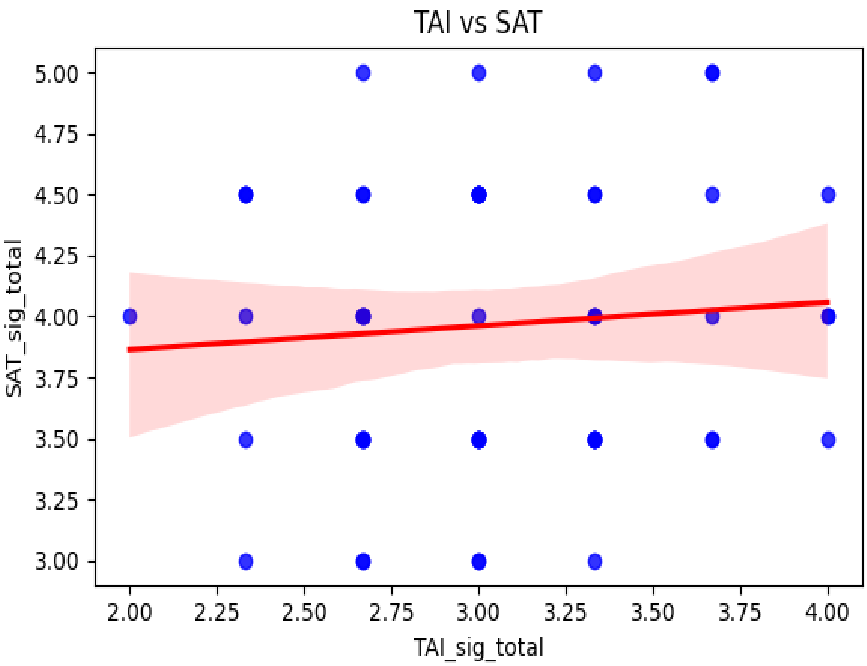

Figure 15. TAI vs SAT

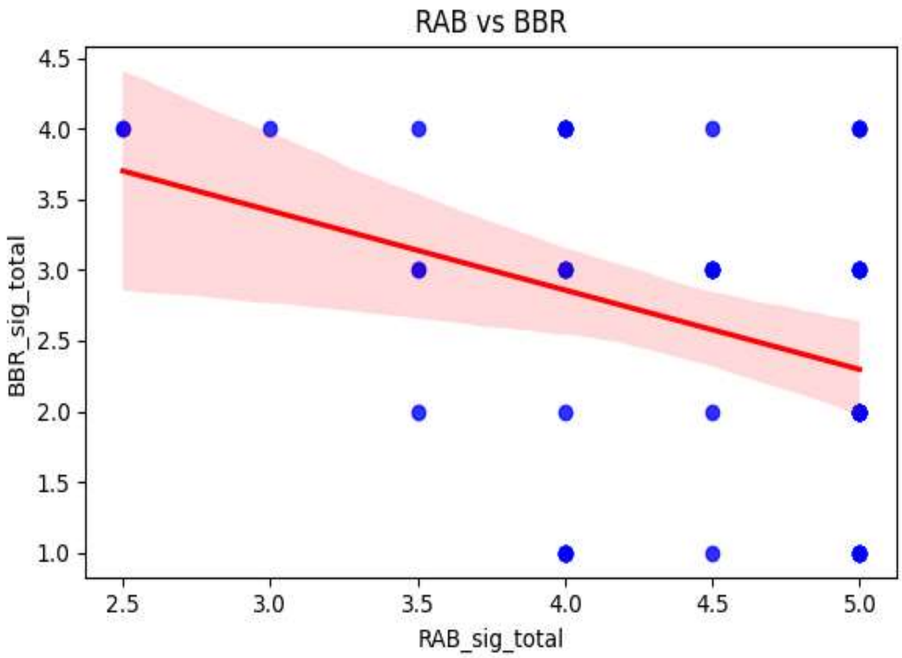

Figure 16. RAB vs BBR

1. RAB vs BBR: Regret Aversion Bias vs Behavioral Bias Reduction

The scatterplot illustrates a **negative linear relationship** between **RAB_sig_total** and **BBR_sig_total**, as shown by the downward-sloping regression line. A higher degree of **regret aversion bias (RAB)** corresponds to a **lower level of behavioral bias reduction (BBR)**.

- The **shaded confidence band** confirms the reliability of this inverse trend despite individual variability.
- This finding underscore **regret aversion as a psychological barrier**, potentially diminishing the effectiveness of AI-driven tools designed to correct cognitive biases.
- It aligns with literature that classifies regret aversion as a **deeply entrenched emotional bias**, often **resistant to automated correction**, and highlights the need for **personalized, emotionally intelligent interventions**, as found in **hybrid AI + human models**.

2. TAI vs SAT: Trust in AI vs Satisfaction

The scatterplot with regression line indicates a **positive but weak correlation** between **TAI_sig_total** (trust or acceptance of AI) and **SAT_sig_total** (satisfaction), consistent with the low correlation coefficient (0.08).

- While greater **AI trust** may be associated with higher **user satisfaction**, the strength of the relationship is **minimal**.
- The wide dispersion of data implies that **satisfaction is influenced by multiple factors** beyond AI acceptance, such as **usability, perceived value, ethical considerations**, and **user expectations**.
- The broad **variability in satisfaction across TAI levels** suggests the presence of **latent moderating variables** like demographics, prior tech experience, or financial literacy.
- The **confidence interval** around the regression further illustrates the **non-robustness** of the relationship, warranting caution in interpreting TAI as a strong predictor of satisfaction.
- From a research perspective, this encourages the use of **interaction terms** or **non-linear modeling** to better capture the complexity of the relationship.

3. TAI vs BBR: Trust in AI vs Behavioral Bias Reduction

The final scatterplot presents a **positive linear trend** between **TAI_sig_total** and **BBR_sig_total**, suggesting a directional relationship where **higher tech adoption is linked to greater behavioral bias reduction**.

- The **moderate to weak strength** of the trend is evident from the **spread of data points**, particularly the clustering around discrete Y-values, suggesting the possible use of **ordinal or categorical rating scales** for BBR.
- The **regression confidence band** remains moderately wide, reflecting variability in prediction accuracy, particularly at the extremes.
- The **distribution of data at integer levels** on both axes supports the assumption of **non-continuous data**, which may limit the interpretive power of standard linear regression.

Interpretation:

- While there is evidence supporting the **positive impact of AI adoption on bias reduction**, the modest strength suggests the influence of **additional mediators**, such as **organizational readiness**, **implementation quality**, or **external market conditions**.

- From a strategic standpoint, the findings support **continued investment in technology adoption**, but with the understanding that **contextual and structural factors** significantly shape outcomes.

VI. RESULTS

The results of this study reveal a compelling and multifaceted picture of how regret aversion bias manifests among urban middle-class investors and how artificial intelligence (AI)-driven portfolio rebalancing strategies can effectively mitigate this behavioral tendency. The initial phase of the research, based on survey data from 58 participants, confirmed the widespread prevalence of regret aversion across key investment behaviors. A significant proportion of respondents reported holding losing investments too long, exhibiting reluctance to realize losses, and delaying reentry into the market after downturns—each of which was shown to adversely impact annual returns. These behavioral patterns were particularly acute among novice investors, suggesting that experience plays a crucial role in reducing emotional decision-making. Furthermore, education level also appeared to correlate with decreased bias intensity, reinforcing the protective influence of financial literacy.

The experimental simulation phase of the study offered direct evidence of the behavioral and emotional advantages of AI-assisted portfolio management. Participants using AI systems demonstrated significantly more optimal rebalancing frequencies, especially during periods of market turbulence. In contrast to the manual group, which consistently underperformed in rebalancing after sharp market movements, AI-guided participants responded in near alignment with optimal benchmarks. More strikingly, those using AI systems required considerably less time to make decisions, reported lower levels of anxiety, and expressed higher levels of confidence in their choices. These outcomes suggest that AI plays a dual role—not only enhancing strategic decision-making but also cushioning the emotional stress that often accompanies complex financial decisions.

A comprehensive analysis of historical portfolio data from 2015 to 2025 further supported the superiority of AI-driven rebalancing strategies. Among the four portfolio types analyzed—Chase Portfolio, Traditional Annual Rebalancing, Traditional Quarterly Rebalancing, and AI-Driven Dynamic Rebalancing—the AI portfolio consistently outperformed across all performance metrics. It produced the highest annualized return and the strongest Sharpe ratio, indicating efficient risk-adjusted returns. Additionally, the AI strategy demonstrated the lowest maximum drawdown and the shortest recovery time following market losses, highlighting its capability to preserve capital and rebound effectively during periods of downturn. By contrast, the Chase Portfolio, which reflected more emotion-driven management, exhibited the worst performance in both volatility control and recovery, thereby validating the risk of unstructured, reactive investment behavior.

In examining the relationship between AI guidance and emotional trading patterns, the data showed that portfolios managed without a structured rebalancing plan were far more likely to deviate from optimal asset allocations and generate unnecessary portfolio turnover. Self-directed investors made significantly more trades driven by emotion rather than strategy, reinforcing the need for consistent, logic-based decision frameworks like those embedded in AI systems. Conversely, AI-guided portfolios not only maintained tighter alignment with strategic targets but also drastically reduced the number of emotionally triggered trades.

The study also explored how different types of AI platforms performed in mitigating specific behavioral biases. The findings clearly indicated that hybrid systems—those combining AI with human oversight—were the most effective at reducing common investor biases, including regret aversion, disposition effect, mental accounting, and herding behavior. Machine learning models performed better than rule-based systems but were still outpaced by the hybrid approach, which delivered the most consistent and balanced performance across all bias categories. These results suggest that human involvement adds an important layer of contextual judgment and emotional guidance that complements algorithmic efficiency.

Further insights emerged from the study's analysis of trust and satisfaction levels among investors using AI-based rebalancing platforms. Trust in AI systems was strongly influenced by the presence of transparency, effective error correction, and especially human oversight capabilities. These features aligned with the most highly rated aspects of AI systems and were predictive of higher adoption likelihood. Satisfaction levels were highest in areas such as return performance, emotional relief, and time savings, indicating that investors not only appreciated the financial benefits of AI but also valued its ability to reduce stress and free up time. Interestingly, satisfaction ratings for personalization and cost-effectiveness were lower, pointing to areas where AI platforms might need further development to meet investor expectations.

The regression analyses provided strong empirical backing for the psychological and behavioral dimensions of these findings. The models predicting regret aversion, trust in AI, satisfaction with AI tools, and perceived behavioral bias reduction all demonstrated high explanatory power, with R^2 values ranging from 0.79 to 0.92. In particular, the perceived reduction of regret aversion emerged as the most significant predictor of an investor's sense that their biases were being addressed effectively. Trust in AI was most closely tied to transparency, error correction, and the ability for human intervention—highlighting the elements that make AI systems feel accountable and safe to users. Meanwhile, satisfaction was most strongly driven by investment returns and emotional management, confirming that users care deeply about both outcomes and experience.

The cumulative growth graphs added a longitudinal perspective to these insights, showing that AI-driven portfolios not only outperformed in individual metrics but also sustained superior value over time. Whether viewed monthly, quarterly, or semi-annually, the AI-based strategy delivered steady, compound growth with less volatility, whereas emotion-driven portfolios like the Chase model exhibited short-term peaks followed by steep declines, and traditional strategies showed stable but limited growth. This further validates the long-term effectiveness of AI-based rebalancing as a solution for both financial performance and behavioral discipline.

VII. CONCLUSION

This research provides robust evidence that regret aversion, a deeply ingrained emotional bias, significantly undermines the portfolio management decisions of urban middle-class investors. Manifesting in behaviors such as the unwillingness to sell underperforming assets or the hesitation to re-enter the market after downturns, this bias results in measurable financial underperformance. Through both survey and experimental findings, it becomes evident that this behavioral tendency is especially pronounced among novice and less-educated investors, underscoring the need for interventions that not only educate but also support investors during moments of uncertainty and vulnerability.

Artificial intelligence emerges in this study not merely as a technological innovation but as a behavioral ally—capable of reducing emotional frictions and guiding investors toward more rational, data-driven decisions. Across performance metrics, AI-driven portfolio rebalancing outperformed traditional and emotionally guided approaches in terms of return, risk management, and recovery. However, the true strength of AI lies in its ability to stabilize decision-making processes. By reducing anxiety, accelerating decision time, and increasing investor confidence, AI systems effectively dismantle the emotional barriers that lead to suboptimal outcomes.

What sets the most successful models apart is not just their algorithmic sophistication but their **integration with human oversight**. The hybrid AI + human approach consistently outperformed both rule-based and machine learning systems in mitigating behavioral biases. This combination of machine efficiency and human empathy appears to be uniquely equipped to confront and correct deeply rooted emotional distortions like regret aversion. It supports the broader behavioral finance proposition that while cognitive errors may be predictable, they are not always correctable through automation alone. Human judgment adds the ethical, contextual, and psychological nuance that algorithms currently lack.

From a practical standpoint, the study also sheds light on the conditions necessary for building investor trust in AI systems. Transparency, clear explanations, robust error handling, and the ability to involve a human advisor when needed were all shown to be critical trust drivers. Without these, even the most sophisticated AI systems may fail to gain widespread adoption. Importantly, investors who trusted the AI system more were also more likely to perceive it as helpful in reducing biases and improving outcomes.

In terms of satisfaction, investors responded most positively to dimensions that addressed emotional and experiential factors, such as time savings and emotion management. This finding reveals a deeper psychological insight: investors are not only seeking returns, they are seeking **emotional security**—a sense of control, predictability, and relief from stress. AI systems that can provide these emotional benefits, in addition to financial performance, are far more likely to be embraced.

Overall, this research contributes significantly to both academic understanding and real-world application. It establishes a strong empirical link between regret aversion and portfolio underperformance while demonstrating the effectiveness of AI—especially hybrid systems—as a solution. It advances the field of behavioral finance by showing that emotional biases can be systematically identified, measured, and mitigated through technology when designed with psychological awareness and human integration in mind.

For financial advisors, platform designers, and policy-makers, the implications are clear: successful adoption of AI in investment management depends not only on technological accuracy but also on **behavioral design and emotional intelligence**. Systems must be built to accommodate human flaws, not ignore them. The future of investing will be shaped not just by machines that think faster, but by technologies that understand the people who use them.

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